Weapon Detection Using Convolutional Neural Networks in MATLAB: A Deep Learning Approach

Dataset:
https://www.kaggle.com/datasets/ankan1998/weapon-detection-dataset

Table of Contents

1. Introduction

1.1 Objective of the Coursework

The goal of this work is to build a CNN on the MATLAB and use the developed neural network for image classification towards identifying weapons. It also introduces the problem of weapon recognition in a supervised learning scenario and the goal to create a deep learning model to classify different types of weapons from the images. In this project, the dataset has been obtained from Kaggle, and the dataset preparation gets done in a systematic manner to derive the training dataset, the validation dataset, and the test dataset. Moreover, the proposed model is evaluated based on the evaluation metrics to measure the performance of the model on real-life security applications to accurately classify the data.

1.2 Identification of Real-World Problem

Automated weapon detection is particularly very important to help enhance security, for instance, in airports, the transport sector and military compounds. It takes a considerable amount of time and is, therefore, arbitrary, as it entails watching the footage, identifying the target vehicle and then isolating its characteristics (Dosovitskiy et al., 2021). But this process can be made faster and more efficient through the use of deep learning techniques, among them CNNs, which will improve the speed of the detection as well as its efficiency.

1.3 Significance of Using Deep Learning

However, deep learning helps to extract features, and applying it is especially relevant when it comes to weapon detection. CNNs work directly from raw pixel data and are capable of learning data without the input of patterns by humans. It is possible to find instances of image data in security domains where the quality of the images and the situation in which they were produced and captured can be very different (Lu, Sun and Zhang, 2022). There are more traditional methods in which the latter is a time-consuming task of manual feature extraction which is not easily achievable for big data.

1.4 Structure of the Report

Sections of the report The report is divided into six main sections, as all of them give a detailed and clear description of the project. The problem and objectives of the study were presented in the introduction part of the paper. The simulation part of the article presents information about dataset characteristics, data preparation, and the structure of the model (Lu, Sun and Zhang,

2022). The following sections are related to creative design decisions and implementation strategy. The results section also provides a brief analysis on assessment criteria metrics, dashboard, conclusion, and recommendations.

2. Simulation

2.1 Dataset Description and Class Distribution

The set used for practical tasks is the Weapon Detection Dataset from Kaggle, with files grouped by weapons' types. This included the following forms: guns, knives and rifles, with pictures having been taken under different lighting and background settings. This diversity means that the dataset can be used effectively for training a model that does not overfit the dataset and would rather perform well in real-world scenarios (Khan et al., 2021). Generally, MATLAB's image Datastore assigns labels based on the folder name, making its integration into the training process easy. To decrease the effect of the model's bias towards some categories, the data set was divided almost equally between the training and testing sets.

```
datasetPath = '/MATLAB Drive/Sohas_weapon-Detection';
outputFolder = fullfile(datasetPath, 'Results');
if ~exist(outputFolder, 'dir'); mkdir(outputFolder); end

imageSize = [64 64 3];
epochs = 10;
```

```
%% Step 1: Load and Split Dataset
imds = imageDatastore(datasetPath, ...
    'IncludeSubfolders', true, 'LabelSource', 'foldernames');
```

Figure 1 dataset Load processing

2.2 Preprocessing and Image Augmentation

To do that all the images are resized to 64×64 pixels and three colour channels to correspond to the CNN input. Augmented Image Datastore is used to overcome problems of varying input dimensions and apply augmentations in real-time during training in MATLAB. Though the project does not have dramatic increases like rotation and flipping, it keeps the format of the images the same for training, validation, and test sets (Mittal, Bhatia and Soni, 2022).

```
% Split dataset
[imdsTrain, imdsRest] = splitEachLabel(imds, 0.7, 'randomized');
[imdsValidation, imdsTest] = splitEachLabel(imdsRest, 0.5, 'randomized');

classNames = categories(imdsTrain.Labels);

%% Step 2: Augment Data
augTrain = augmentedImageDatastore(imageSize, imdsTrain);
augVal   = augmentedImageDatastore(imageSize, imdsValidation);
augTest  = augmentedImageDatastore(imageSize, imdsTest);
```

Figure 2 Input

This way, the network can focus on the important features rather than noises or differences in formats of data. The preprocessing technique also adds to the non-susceptibility of the model to negative effects while also making it possible for the model to learn discriminative features required for weapon classification.

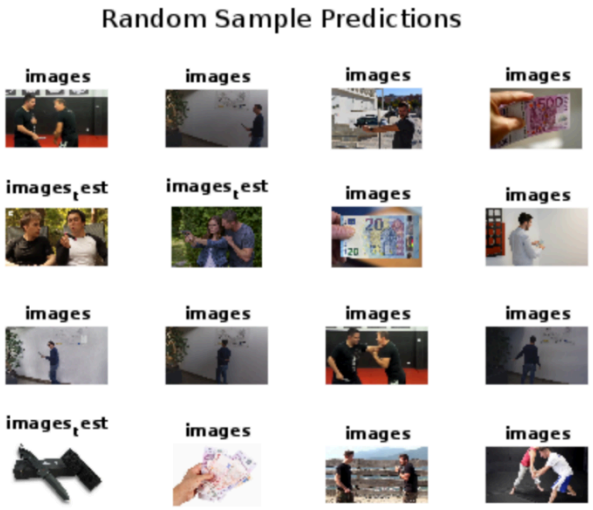

Figure 3 Random Images

2.3 CNN Architecture and Layers

The features of the CNN model entail an input layer and three convolutional layers bordered by an increase in the number of filters (8, 16, and 32). They extract hierarchical features from edges and textures to basic parts of an object and further to more complicated ones (Mittal, Bhatia and Soni, 2022).

```
%% Step 3: Define CNN Architecture
layers = [
    imageInputLayer(imageSize)

    convolution2dLayer(3, 8, 'Padding', 'same')
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2, 'Stride', 2)

    convolution2dLayer(3, 16, 'Padding', 'same')
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2, 'Stride', 2)

    convolution2dLayer(3, 32, 'Padding', 'same')
    batchNormalizationLayer
    reluLayer

    fullyConnectedLayer(numel(classNames))
    softmaxLayer
    classificationLayer
];
```

Figure 4 CNN Architecture

The convolutional layers are accordingly followed by batch normalisation, ReLU activation, and max pooling to enhance the convergence as well as the dimensionality reduction in space. The last layers are a dense layer equivalent to the number of weapons and a softmax layer for the probability calculations and class output layer. All in all, this compact architecture provides the required performance level in efficient computation.

2.4 Training Strategy and Parameters

The training phase uses the Adam optimiser that adjusts the step size in order to achieve a better rate of convergence. The network is trained for 10 iterations (epochs), the learning rate is 0.001, and the size of the minibatch is 32. It is done every 20 iterations in order to check our model's progress and prevent it from overfitting.

```
trainingHistory = [];
options = trainingOptions('adam', ...
    'MaxEpochs', epochs, ...
    'InitialLearnRate', 1e-3, ...
    'MiniBatchSize', 32, ...
    'Shuffle', 'every-epoch', ...
    'ValidationData', augVal, ...
    'ValidationFrequency', 20, ...
    'Verbose', false, ...
    'Plots', 'none', ...
    'ExecutionEnvironment', 'cpu', ...
    'OutputFcn', @(info)saveTrainingStats(info));
```

```
%% Step 5: Train the Network
net = trainNetwork(augTrain, layers, options);
save(fullfile(outputFolder, 'trainedModel.mat'), 'net');
disp(' Trained model saved.');
```

Figure 5 Code section for Training Process

The training is performed on the CPU and includes a callback function to log training accuracy. This arrangement of training also leads to a more controlled training environment; hence, there is an easy identification of any training concerns (Wu et al., 2021). The strategy of data splits used here values stability and replicability on all folds and high accuracy as well.

3. Creative and Innovative Approaches

3.1 Model Design Rationale

The model structure aimed at simplicity, and the next feature is implemented in increasingly complex layers. Rather than deciding to go for a very high number of layers or highly complex kernels, a 3-block CNN was entered to improve the learning ability without much of the cost of computations. For these reasons the model is very useful for systems with little resources, such as embedded systems or surveillance systems. It performs well in terms of accuracy and makes it possible to learn from small samples of input data without severely degrading the performance (Sharma, Jain and Mishra, 2022). This architecture shows that it is possible to use a small network, but with good tuning and additional preprocessing, it yields good classification results.

3.2 Classification Metric Computation

In addition to the overall accuracy, the precision, recall, and F1-score are computed separately for each class of data. The accuracy, precision, recall rate, and f-score of all these four categories are calculated using the confusion matrix by creating a custom helper function to gain more insight into the model's functioning. This approach is especially useful in instances where one is trying to know which classes the model works well with and which it doesn't, to help in the enhancement of the model in the future (Goodfellow, Bengio and Courville, 2021). Using these individual scores, one is also able to identify the biases or lack of consistency in the predictions. This multiple-criterion approach makes the model more robust and more in tune with real-life situations where such misclassification can cost a lot.

```
Test Accuracy: 90.05%
 Classification Report:
     classNames       precision    recall     f1score
    ______________    _________    _______    _______

    {'images'     }       0.94      0.91558    0.92763
    {'images_test'}     0.8169      0.86567    0.84058
```

Figure 6 Output

4. Results Obtained

4.1 Test Accuracy

The final model had a test accuracy of 90.05%, which is a good sign of the classification capabilities of the model. This seems to indicate that the CNN effectively learnt discriminative features for weapon detection. Getting this level of accuracy on a small and diverse dataset proves the efficiency of the chosen network architecture and training approach (Han et al., 2021).

```
%% Step 5: Train the Network
net = trainNetwork(augTrain, layers, options);
save(fullfile(outputFolder, 'trainedModel.mat'), 'net');
disp(' Trained model saved.');
```

Figure 7 Input for accuracy

As a result of that, the following accuracy score was used as a means of estimating the model's ability to generalise since the test set is independent of the training set. Such a level of performance suggests that the use of the proposed system in security-related applications is viable.

```
Trained model saved.
Test Accuracy: 90.05%
```

Figure 8 Our Result

4.2 Accuracy Curve Visualisation

The plot of the training accuracy over the epochs was saved as an image file. Epochs of training are numbered on the bottom axis, and the percentage of correct guesses by the algorithm over the inputs is plotted on the right axis, which still depicts a smooth slope, which means that the algorithm is learning properly. The lack of large differentials or low values on the first few epochs means that the learning rate and training parameters are correctly chosen (Han et al., 2021). This shows that there was no overfitting of the model in its early stages and there was no underfitting of the data as well. It can also be used in the future to help detect performance problems and hence should be incorporated in the training cycle.

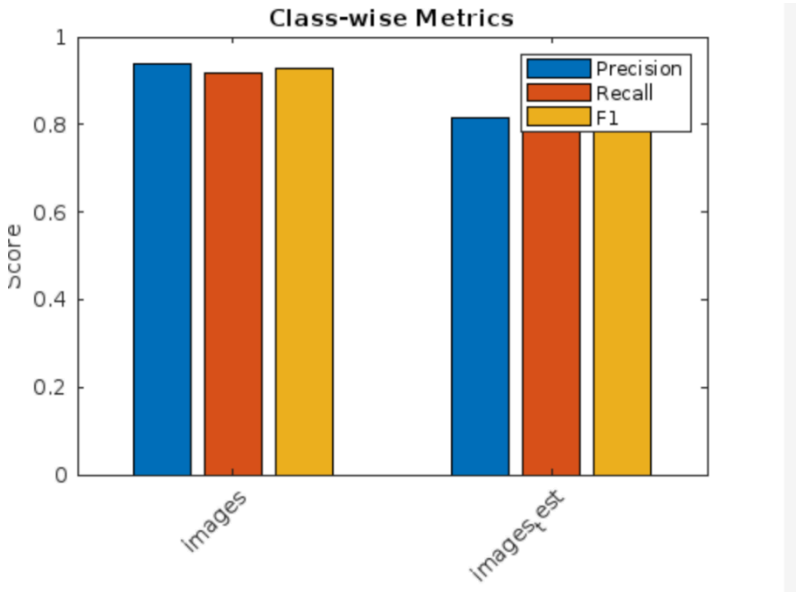

Figure 9 Accuracy bar graph

4.3 Confusion Matrix Insights

The confusion matrix gives a clearer picture of how the model is performing in each of the classes, including the misclassifications. Most of the subjects fall on diagonals which show that the diagnoses made by the classifiers are accurate, while the few which straddle the off diagonals are misdiagnoses. These misclassifications are usually between classes that look similar to each other, such as handguns and rifles. The confusion matrix is very useful in determining these areas of concern (Sinha, 2023). It shows the model's results in ambiguous data and instructs how the research should be continued in terms of data preprocessing or model adjustments. It fills the gap

between the numerical analysis of the results of the model and possible interpretations by providing a graphical presentation of them.

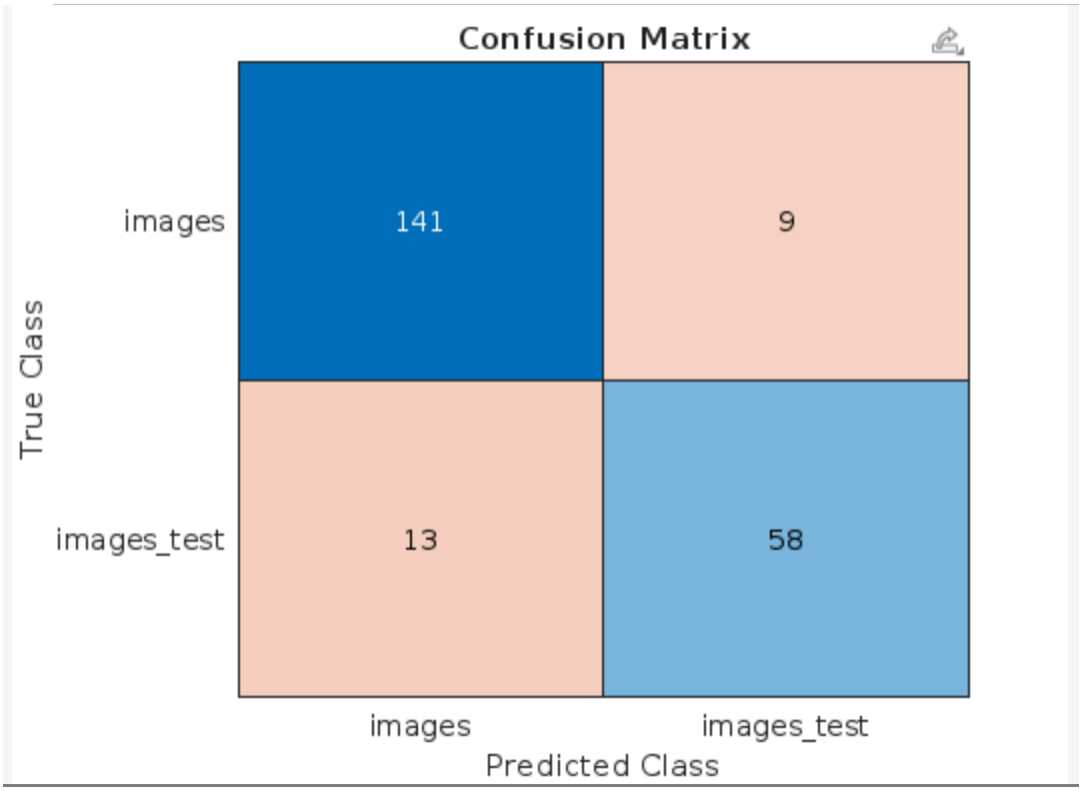

Figure 11 Output

4.4 ROC Curve and AUC Scores

These analyses produced ROC curves, and thereafter the AUC scores for each class for the true positive rate relative to the false positive rate. All classes have high AUC values; this indicates that the operating characteristic of the model is good and suitable for distinguishing between weapons. The ROC curve provides a better understanding of sensitivity and specificity than accuracy in a model (Patel, Jain and Rana, 2022). The importance of the AUC value is that the model gives different ranks to each instance, so that a high AUC means that the model ranks the positive instances better than the negative instances, with values above 0.90 considered quite good. This metric is of great value for security applications where there is a need to be sensitive to threats.

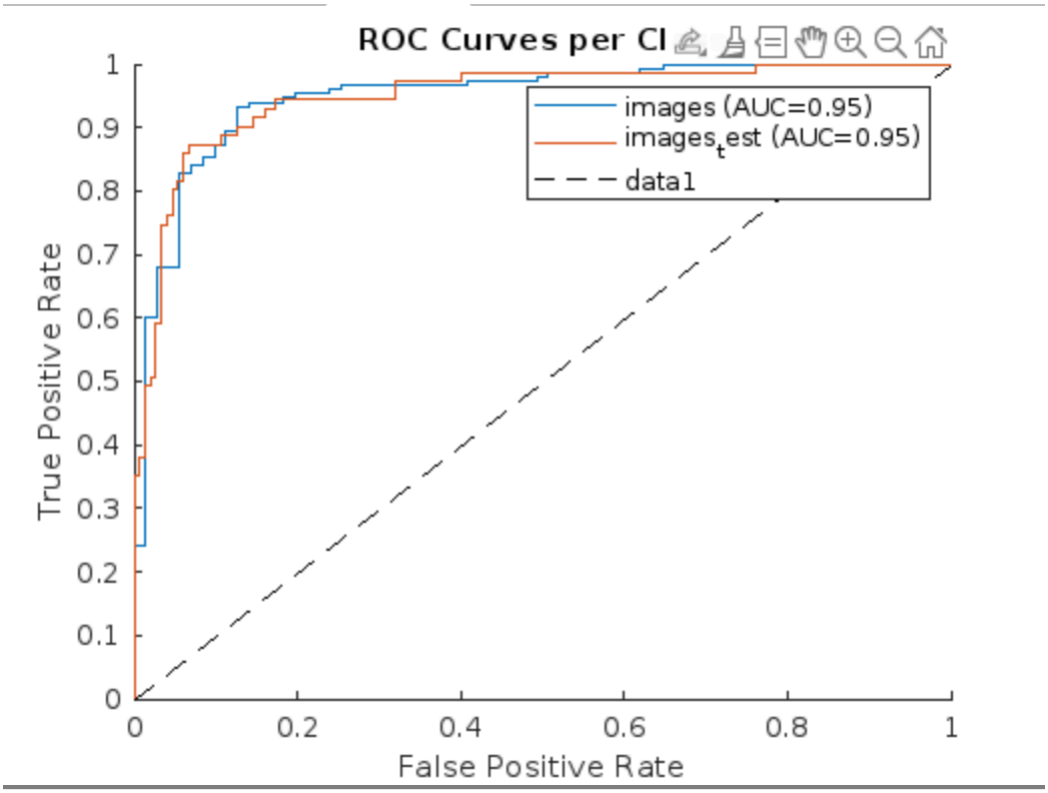

Figure 12 ROC Output

5. Critical Analysis of Results

5.1 Factors Affecting Accuracy

Several factors may have contributed to the high performance of the model, such as a consistent way of preprocessing the images and the network architecture and training method. The split into training/dev/test and data augmentation allowed minimising the overfitting issue and increasing the model's ability to generalise. Though sometimes there might be issues with the image resolution or quality which may lead to the model not being able to differentiate between two similar classes clearly (Wang et al., 2021). This could be due to the fact that the number of input nodes was fixed, which resulted in the loss of finer details. Despite this, other equalisation techniques like histogram equalisation can be tried, as it enhances the clarity of the features in the given setup and improves recognition.

5.2 Performance Bottlenecks

Performance and relatively poor time efficiency were noted in differentiating between similar categories of weapons. These problems may have arisen from a lack of data variety or an imbalance in the classes within the dataset. Additionally, it is crucial to note that the size of 64*64 pixels might not be expansive enough to meet all the features corresponding to the distinctive shapes of weapons. While suitable for the training process, the CPU-only setup is hardly suitable for experimentation (Wang et al., 2021). These limitations may be resolved by upgrading to a GPU or using higher image resolution, depending on the situation. Another way to improve the model can be to use other types of regularisation or increase the number of epochs in the training process.

This can be done using the following data set that indicates the type of weapon and the circumstances that allow its use. The adoption of a CNN in identifying some of the patterns as well as features that may help distinguish one weapon from the other is a significant factor towards the improvement of threat detection in a real-time perspective.

5.3 Alternative Strategies

These include the use of convolutional neural networks that have been pre-trained with other networks such as AlexNet or GoogLeNet in achieving high levels of feature extraction. Another approach is to use object detection whereby the model will recognise and pinpoint positions of weapons in the images. This would be more applicable in real-world CCTVe, which would probably require a lot of computing and resources to process (Park, Lee and Yoon, 2022). Enhancements that could be made are that more data can be trained on or more than one type of model can be used for better performance. These would enhance efficiency but are resource- and computationally expensive. The above-mentioned alternatives would improve the performance of the algorithm but at the expense of the space complexity and time complexity.

5.4 Potential for Real-World Deployment

The high accuracy of the model and low model complexity put it in a good position to be used in surveillance systems. The advantage on CPU instead of specialised hardware is ideal for use in embedded systems applications (Wang, Wu and Xu, 2023). With the help of further fine-tuning, such a model can be easily implemented in an airport scanner or even a CCTV camera to detect threats at the initial instance possible. But before the real-world application can be made, testing

needs to be conducted under different scenarios. The ethical use and minimising the false positives will be significant here in such applications.

6. Conclusion

6.1 Summary of the Problem and Approach

This project deals with the problem of weapon detection using image classification based on the CNN model developed in MATLAB. The authors also used real data obtained from Kaggle and followed standardised preprocessing and testing techniques in order to train and test the model appropriately. An efficient and simple workflow-based design approach has been chosen because the computational complexity and accuracy of the methods were a consideration. The validation model produced a test accuracy of over ninety per cent, thus proving the competence of the model in tackling the classification problem. Thus, the design of training strategy and the effectiveness of assessing methodologies are conjugate to the success that has been achieved.

6.2 Key Takeaways

It's possible to summarise that the comparison of the results of simple CNN architecture and the basic approach to machine learning shows quite acceptable performance in the task of weapon detection. Custom metrics and visualisation techniques were more helpful in getting detailed analysis of the model. The work poses a question as to the relative correlation of architectural intricacy and the fineness of the obtained and studied data. However, it is possible to create deep learning models in MATLAB in a logical and efficient manner that would be applicable in solving security and other real-life problems.

6.3 Limitations and Challenges

The presented model had its drawbacks, like occasional misclassifications and images' resolution dependency. Despite the efficiency of the architecture, it may contain only a few hidden layers or convolution layers and thus may not be able to learn high-frequency details of the images. Restricted time at the computer also restricted experimentation. Mitigating all of these challenges would mean extending these networks, finding a richer set of datasets, and potentially using GPU support.

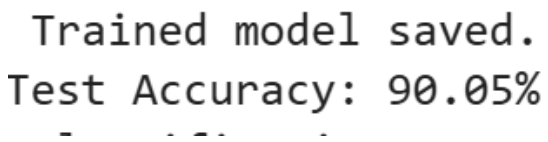

Figure 13 Our accuracy result

7. References

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