Gun model classification based on fired cartridge case head images with Siamese Networks

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Abstract. The identification of the firearm model that triggered the firing of a bullet is an important forensic information that, historically, has been done by trained examiners through visual inspection using microscopes. This is an extensive and very time-consuming process that requires the examiners to be trained to identify and compare the fired cartridges. This paper proposes an automated objective method for binary classifying pairs of fired cartridge head images as belonging to the same or different classes, using siamese neural networks (SNNs). With this technique, an accuracy of up to 70% was reached by using firing pin mark images as the input of the SNN. For the training and optimization of the network this paper also analyses and presents different image preprocessing approaches.

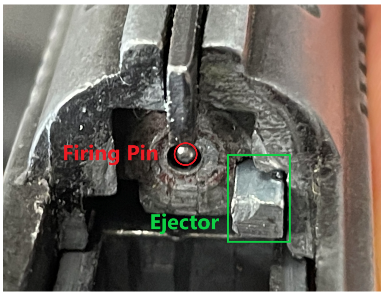
Keywords: Siamese Neural Networks, Image preprocessing, Firearm model classification

1 Introduction

When a hard surface comes into contact with a softer surface, plastic deformation occurs [1]. In the context of ballistics, the deformation produced in a bullet or its casing when firing a projectile is unique to each weapon. Thus, the marks imprinted by weapons on the surfaces of a bullet or casing allow identification of the model of the weapon that fired it [2]. Figure 1a depicts the weapon parts that leave marks in the head of the fired cartridges.

At the Portuguese Criminal Police (PCP) or Polícia Judiciária, the process of identification of the firearm model based on the cartridge case head is carried out by the ballistics experts, comparing the marks found on the cartridge case head being analysed with marks found on multiple other cartridges case heads from multiple different gun models, using microscopy.

The goal of the examiners is to find consistent marks between the analysed target and reference cartridges. The characteristics the experts look for include: the shape of the firing pin impression, firing pin marks, breech face marks, shape and location of the ejector mark and others. For this analysis, examiners control the lighting conditions and the magnification of the lens they are using. This type of imaging can be seen in figure 1b.



(a) Examples of gun parts that may leave marks on the cartridge

(b) Microscopy analysis

Fig. 1: Bullet chamber and fired cartridge case head

According to the PCP, this process, when done manually, has a success rate of 16%. It is a very time-consuming task for the examiner, requiring the handling of multiple specialized equipment and taking the various necessary steps in order to correctly collect and analyse the samples. Aside from these, it is also required that the specialists are very well trained on how to inspect and compare the specimens, as well as have the knowledge of what to look for when doing such task.

In this paper, the viability of the use of a siamese neural network to train a model that can discriminate whether two different images of cartridge case heads belong to the same model is analysed, using a dataset provided by the PCP. With such a model, it will be possible to create a tool that can help the examiners do their work more efficiently by providing them with the most likely firearm models that fired the bullet from the cartridge being analysed.

2 Literature Review

Automatic identification of firearms models using Machine Learning

This LR was performed in the research related topic of Automatic identification of firearms models using ML.

The selection of studies for this analysis was conducted considering two important aspects of this work: The use of Machine Learning in the automatic identification of firearm models based on images of spent cartridges and the image processing techniques used to process cartridge images.

During this search, it was observed that most of the papers had referenced image processing techniques for the preprocessing of the ballistic imaging. This emphasises the importance of reviewing these techniques when researching Neural Networks for ballistic applications.

Regarding Image processing techniques, Gerules et al. [3] states the importance of the use of image preprocessing for correction of acquisition defects or image enhancement for "later processing of other algorithms". Some techniques used for this purpose are described, those include: "Elementary image processing operations" which are based on "pixel level operations" and "Higher-order image processing operations", which include various techniques that can improve quality of processing "by accounting for larger neighborhoods". In [4], Huang et al. develops a binarization algorithm for edge detection and compares it to previously proposed algorithms: Otsu [5], Chow and Kaneko [6] and Yanowitz and Bruckstein [7]. The algorithm proposed by the authors outperforms the algorithms it was tested against. The same authors, states in [8] that "the purpose of image processing is to extract the interesting features from the cartridge images" and that, to do so, it is required to binarize the images. In their analysis, three edge detection operators are compared and it is found that "the optimal solution can be obtained by combining some steps with Sobel operator and Canny operator".

Regarding the use of Machine Learning in the identification of firearms it was found that in 2011, Kamaruddin et al. [9], tried using firing pin based geometric moments proposed by Ghani et al. [2] in 2010 to train a back propagation neural network with the "trainlm" algorithm and a 6-7-5 architecture, achieving 96% accuracy on firearm classification. One year after that development Leng et al. [8] proposed a novel method for feature extraction called the "circle moment invariants". They then used the outputs of this extractor as features to train a 3 layer backpropagation Neural Network, obtaining a 98% accuracy for firearm identification. Most recently, a document written by Giudice et al. [10] suggested the use of breech face only images, generated from 3D point clouds, as input for a siamese neural network. This network showed positive results for a Top-N probability based metric.

The previously analysed techniques show that authors usually approach this problem by first applying some type of preprocessing such as image enhancement, feature extraction or segmentation. Only then, will the results of these procedures be applied to classifier approaches.

Considering the current state of the art, we propose the use of a siamese neural network to solve this problem, as it has never been applied before by the scientific community.

3 Proposed Solution

As a response to the PCP's comparison method, it is proposed that a siamese neural network is developed and trained to classify weather or not pairs of images of cartridge case heads belong to the same firearm. Since the data available per class is limited, as can be seen in table 2, and due to the fact that siamese neural networks allow for the augmentation of the data by forming pairs, we think that this type of network is potentially a good fit for this application. Also, in the conducted research on the topic it was found that the employment of SNN on ballistic identification using images has not been extensively documented and tested, making it an important topic to investigate as it might hold potential in this context. The outcome of this research should be regarded as a means to optimize the examiners search by providing them with pointers of what cartridges to target.

For the development of such Network, it is necessary that a considerable volume of samples are available for training. With this purpose, the PCP has scanned part of its archives and made the data available to researchers.

3.1 Image Acquisition and segmentation

The proposed solution involved the use of the ToolScan imaging system [11] to acquire 2D and 3D images of the multiple fired cartridges in one scan. Besides doing the image acquisition, examiners at the PCP also annotated most of the dataset's images with the cartridge case heads outline, breech face impression, firing pin impression, and ejector mark.

After the scanning of the cartridges, the resulting image is a matrix of casings, as can be seen in Figure 2:

Fig. 2: Scan output image

For the training of the network there was the need of segmenting this image into multiple singular cartridge case head images. To do so manually would be very time consuming. To resolve this issue, the images were automatically segmented by applying a threshold to binarize them and then the Hough Circles algorithm was used to find the cartridges positions. An example with the cartridges suggested final positions is shown in Figure 3:

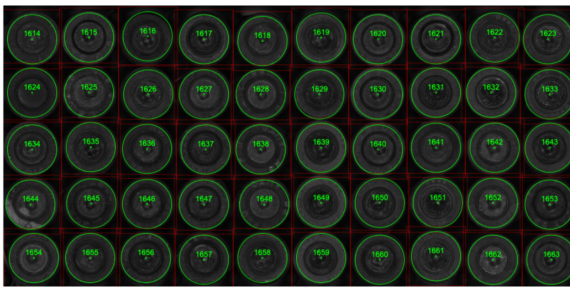


Fig. 3: Proposed Cartridges Positions

The segmentation itself is done with OpenCV based on the circles, a margin of 10% is added to the circle, and a rectangle is cut around them.

3.2 Dataset Characteristics

The available labeled digital archive contains a set of 1295 cartridge case head images distributed through 5 different classes, as can be seen in Table 1:

Table 1: Dataset Characteristics.

Gun model	Number of cartridges	Unique firearms
315 Auto	150	38
950B	149	42
Baby	99	30
Gt28	747	235
P6	150	46

From Table 1 it can be observed that the dataset is considerably imbalanced, considering the high volume of "GT28" cartridge images in comparison to the other classes. Due to the need of balancing the classes for machine learning applications, the amount of images that were used for training was substantially lower than the original dataset, under sampling the majority class(es) (to have the same diversity in each class). Additionally, it is required to divide the dataset in a way that the Training Set, Validation Set and Test Set would not share unique firearms between them. Not doing this, would allow the network to learn the specific characteristics of the Firearms and perform well based on this information, instead of learning the characteristics of the firearms models. After combining the under sampling of the majority class with the need for unique guns in each set, the division presented in Table 2 was used to create train, validation and testing arrays for the SNN:

Table 2: Number of images per set for each class (after under sampling)

Number of images for:	315 Auto	950B	Baby	Gt28	P6	Total
Training	106	94	76	94	84	454
Validation	20	27	14	40	28	129
Testing	24	28	9	42	38	141

3.3 Siamese Neural Networks

This section presents the experimental approaches that aimed to optimize the accuracy obtained by the siamese neural network. The corresponding results are detailed and further discussed in section 4.

A siamese neural network training consists on decreasing the distance between the output of two similar convolutional neural networks, for images of the same class, and increasing it for images of different classes. For this application, with limited available data, this type of network is useful as it works by binary classifying pairs of images instead of singular images, allowing the same data to be used multiple times by combining the dataset's images in many different pairs. This is an important consideration because it allows for the augmentation of the training set that will be the input of the network. In Figure 4, the general architecture of a siamese neural network, as proposed by Koch [12], is presented. In this paper, the SNN's input is the normalized values of the images pixels.

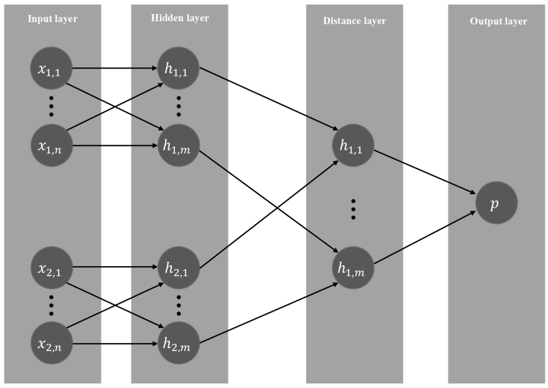


Fig. 4: Siamese Neural Network Architecture

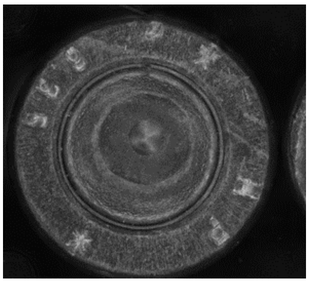
For the development of this Network, Keras Tuner [13], a Pyhton library, was used to generate and Train random Networks within given boundaries. With this tool, the optimization of the network's hyperparameters is done automatically by selecting random values for convolution sizes, number of layers, pooling sizes, number of filters and number of neurons. This random selection is made a parameterizable number of times and the selected network architecture is trained each time. After the end of the parameters search the best performing models are returned.

For the training of the model, the original images had to be resized to a lower resolution that varied between 100x100 px to 400x400 px. Although these lower resolutions are not ideal for images that require the visualization of small details, this limitation had to be implemented considering the hardware being used, that would run out of memory if the arrays contained larger images (Hardware: GTX 1650 mobile - 4GB Vram, 8GB RAM).

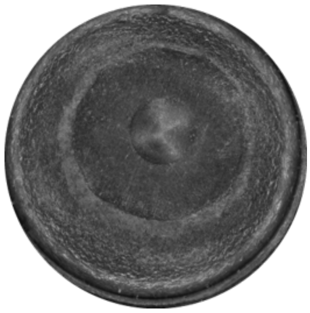
In the beginning of the development of the model, multiple SNNs were generated and trained using the full cropped images in the dataset, as seen in Figure 5a.

It was thought that the use of the breech face only for the input of the neural network would grant good results. The result of the segmentation of the breech face can be seen in Figure 5b.

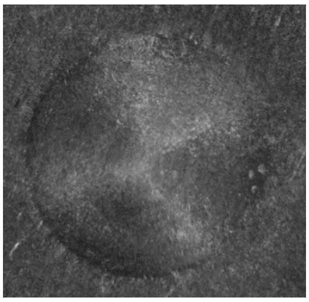
The firing pin impression was considered by Kamaruddin et al. [9] as a valuable feature for firearm identification. Hence, it was extracted from the cartridge image and used to train the siamese neural network. The firing pin impression can be seen in Figure 5c.



(a) Full Cartridge head image



(b) Cartridge head breech face image



(c) Firing pin impression

Fig. 5: Proposed cartridge case head segmentation

3.4 Image Processing

As suggested by studies [3], [4] and [8] analysed in section 2 , the use of image preprocessing is an important step before proceeding with classification techniques. In this section, a simple technique for image enhancement is presented. The images with the filters applied were then used as input to multiple iterations of SNNs.

An attempt to isolate regions of interest was made by developing a binarization algorithm based on the proposed technique presented in [4]. The algorithm used to process the images consisted in:

1. Removing noise with median blur filter 4x4. Median Blur was used because it preserves edges, which are useful in this application;
2. Converting image to Grayscale. Although the images are originally Grayscale, the reading process converts them to BGR;

3. Gamma Correcting images to improve contrast, as some images in the dataset are dark and the binarization algorithm wouldn't perform as desired;
4. Applying Otsu Binarization Algorithm.

The result of this technique can be visualized in Figure 6a. After the creation of the mask, it is applied to the original image. The result of this can be visualized in Figure 6b.

(a) Firing pin mask

(b) Firing pin image with applied mask

Fig. 6: Proposed feature enhancement technique

4 Results

Throughout this research, multiple different SNNs were trained with different approaches to the problem at hand. Table 3 shows the accuracy interval from the various trained neural networks for each approach:

Table 3: Trained networks results.

Approach	Accuracy Interval
Full cartridge case head	49% - 51%
Whole breech face	49% - 51%
Processed firing pin	56% - 68%
Firing pin	59% - 70%

The approach that produced the best results, slightly higher than the firing pin processed images, was the use of the original firing pin segmentation as input to the siamese neural network. The highest accuracy SNN that was trained achieved an accuracy of 70% on the test Set. As we can see in Table 3 all the other approaches showed little potential averaging 50% correct classifications. In the current context, 50% accuracy is viewed as a low score due to the fact that the network outputs binary classification. Although it is surprising that none of the other approaches showed potential this is still a work in progress and more techniques will be tested. The SNN that yielded the best results has the architecture demonstrated in Figure 7.

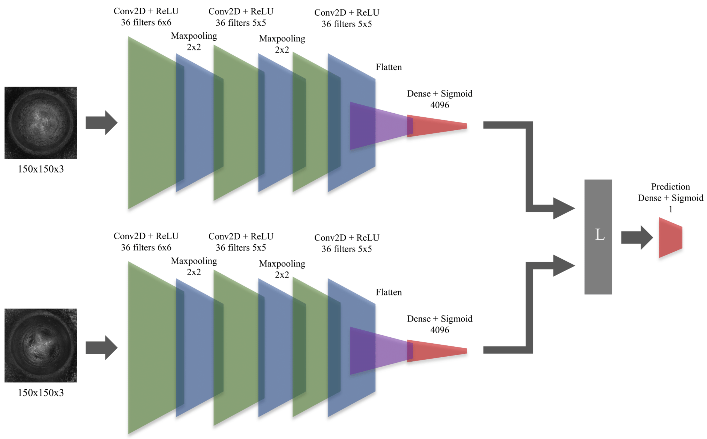


Fig. 7: Proposed Siamese Neural Network Architecture

5 Conclusion

This paper presented the viability of using a siamese neural network model to classify whether two images of cartridge case heads correspond to the same class. This model was designed for and trained with the dataset provided by the PCP. The work that has been presented in this paper allows for the conclusion that the best way to approach this problem is by using the firing pin impression images as input of the neural network. It's also shown that the techniques proposed for image enhancement should be improved on and that the segmentation of more relevant parts of the firearm images can have a very significant impact on the outcome of the solution developed.

The presented work was the first approach on the process of developing a siamese neural network architecture that aims to produce an accurate outcome using images of the cartridge case head, independently of the various different classes it might be trained with. This is one of the initial steps towards the development of a tool that will able to help ballistic experts to target the gun they are looking for more accurately and efficiently, saving human resources. The results achieved represent an early stage of the project and will be improved with further research and testing.

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