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2021-11

Elsevier B.V.

http://hdl.handle.net/10138/347666

Oura, P, Junno, A & Junno, J-A 2021, 'Deep learning in forensic shotgun pattern interpretation-A proof-of-concept study', Legal Medicine, vol. 53, 101960. https://doi.org/10.1016/j.legalmed.2021.101960

Deep learning in forensic shotgun pattern interpretation – A proof-of-concept study

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Compliance with ethical standards

- Conflicts of interest/competing interests: The authors have no relevant financial or non-financial interests to disclose.
- Funding: No funding was received for conducting this study.
- Ethical approval: Not applicable: This study did not involve animals, humans, or human cadavers.
- Consent to participate: Not applicable.
- Consent for publication: Not applicable.
- Availability of data and material: The datasets and algorithms generated and analyzed during the study are available from the corresponding author on request.

ABSTRACT

Little is known about the potential of artificial intelligence in forensic shotgun pattern interpretation. As shooting distance is among the main factors behind shotgun patterning, this proof-of-concept study aimed to explore the potential of neural net architectures to correctly classify shotgun pattern images in terms of shooting distance. The study material comprised a total of 106 shotgun pattern images from two discrete shooting distances (n = 54 images from 10 meters and n = 52 images from 17.5 meters) recorded on blank white paper. The dataset was used to train, validate and test deep learning algorithms to correctly classify images in terms of shooting distance. The open source AIDeveloper software was used for the deep learning procedure. In this dataset, a TinyResNet-based algorithm reached the highest testing accuracy of 94%. Of the testing set, the algorithm classified all 10 m patterns correctly, and misclassified one 17.5 m pattern. On the basis of these preliminary data, it seems achievable to develop algorithms that would serve as a beneficial tool for forensic investigators when estimating shooting distances from shotgun patterns. In the future, studies with larger and more complex datasets are needed to develop robust and applicable algorithms for forensic shotgun pattern interpretation.

KEY WORDS

Forensic medicine, Shotgun pattern, Gunshot interpretation, Deep learning

1. Introduction

Gun-related violence is relatively common worldwide although there is great deal of geographical variation. For example in 2014, there were a total of 30 000 recorded deaths from gunshot trauma in the US [1], a country with nearly half of the firearms in the world [2]. In order to obtain a comprehensive conclusion of events in gun-related violence, it is highly important to extract information regarding, e.g., gunshot trajectory and shooting distance [3–5]) as accurately as possible. Usually, this is achieved by combining evidence from the suspected crime scene and post mortem examination. However, little is known of the potential of artificial intelligence in assisting the forensic and investigative process in gunshot pattern interpretation [6].

There are several types of forensic scenarios involving intermediate-range shotgun wounds. In assault and robbery, shotguns and sawn-off shotguns are utilized as effective close-range weapons. They are also used by police and security personnel in close-quarter contact situations. Shotguns are extremely injurious within shorter distances and with buckshot even up to 150 yards (e.g. [7–9]). Moreover, shotguns are often involved in accidental deaths (e.g. [10]) which may occur, for example, at the shooting range or while hunting.

Shotgun patterning is a result of multiple factors (e.g. [7]). Firstly, shotgun barrel length has a major effect on patterning and short barrels such as in sawn-off shotguns tend to offer a wide spread pattern already from short shooting distances [11, 12]. Longer barrels in turn tend to provide tighter patterns. Secondly, the choke has a major influence on patterning. While full choke is often used by hunters aiming to shoot tight patterns over longer distances, tighter chokes increase the pellet count in the central part of the pattern and scatter pellets at the edges. Cylinder choke has opposite effects, and the pattern should remain relatively even throughout the pattern. In addition to barrel length and selection of the choke, several factors such as bore size, pellet size and material (e.g. lead vs. steel) influence patterning [9].

Previous literature on shotgun pattern interpretation and ballistics is relatively scarce. Interestingly, due to varying pattern structures, shotgun patterns may permit more accurate estimates of shooting distance than bullet wounds of rifles and handguns [7, 13]. This primarily applies to ranges above 6 meters as closer-range shots cause similar trauma to an individual missile [14]. Given the strong visual nature of data related to shotgun patterning, artificial intelligence may prove useful in shotgun pattern interpretation.

Deep learning is an artificial intelligence approach that uses trained neural networks in a wide range of concepts such as image recognition [15–17]. In this proof-of-concept study, we tested whether deep learning-based algorithms are able to predict shooting distance on the basis of shotgun patterns between two relatively close alternatives. We utilized a preliminary dataset of 106 shotgun pattern images (54 from 10 m and 52 from 17.5 m) to test the potential of neural net architectures in shooting distance classification.

2. Materials and methods

2.1 Study material

The material of this proof-of-concept study comprised a total of 106 shotgun patterns from two discrete shooting distances recorded on blank white paper. The experiments were performed in a restricted area by a researcher with a valid firearms license and long-term experience with firearms (JAJ). Ethical approvals were not required as animals, humans or human cadavers were not involved due to the preliminary nature of the study.

2.2 Shotgun patterns

Due to the preliminary nature of the study, all circumstantial factors were fixed except for shooting distance. Two shooting distance classes were selected according to the potential use of a shotgun as a deadly close-range weapon. The first distance was 10 meters, ensuring that in most cases all of the pellets had already left the plastic, cuplike shotshell wad, and provided clear pattern with all of the pellets clearly separated. The second shooting distance, 17.5 meters, provided just a minor increase in distance but with cylinder choke, the pattern would be already wider when compare to shooting distance of 10 meters. Importantly, we wanted to keep the size of the pattern within the size of an average adult human torso, and thus 17.5 meters appeared as an optimal alternative.

To inflict the patterns, we utilized Benelli (Urbino, Italy) Montefeltro Synthetic 12/76 semi-automatic shotgun with Aimpoint (Malmö, Sweden) Micro S-1 red dot sight. A 28" barrel length and cylinder choke were used in this study. Ammunition was Winchester Super Speed 12/70 (2¾") with 36 grams of 3.1 mm (number 4) lead pellets. The reported velocity of the pellets was 417 m/s, actual velocities were not measured. The shell selection was based on the general popularity of the shell brand, pellet size, and weight of the load. We hypothesized that this shotgun and ammunition combination would represent a typical case of an accidental, lethal gunshot. Buckshots and other large diameter pellets were not selected for this study as their patterning would potentially be more difficult to assess.

Cylinder choke was chosen for this proof-of-concept study as we wanted to examine patterning at the shooting distances that are typically lethal in both accidental and intentional gunshots. However, as we were interested in the pattern, we hypothesized that cylinder choke would provide distinct patterns already from relatively short distances. Shooting target was a blank white paper of 100 cm in diameter. Shots were fired horizontally in a 90-degree angle to the paper target.

2.3 Photography and post-processing

Shotgun patterns were photographed using a professional 24.2-megapixel digital single-lens reflex Canon EOS 77D camera with Canon EF-S 17-55 mm f/2.8 IS USM lens (Canon, Tokyo, Japan). Photographs were taken in a 90-degree angle towards the paper, ensuring an even lighting. The external circumstances such as weather and lighting remained unchanged over the experiment.

Photoshop Elements version 2020 (Adobe, San Jose, CA, USA) was used to crop and process the raw full-sized photographs obtained during the experiment. First, each pattern was cropped individually with a rectangular cutter tool along the edges of the pattern. Then, the minor shadows and edges of the paper were faded using the “lighten shadows”, “midtone contrast” and “auto levels” tools. Photography and post-processing were identically performed for the 10 m and 17.5 m images. Examples of the extracted images are presented in **Figure 1**.

2.4 Deep learning procedure

For the deep learning procedure, the shotgun pattern images were randomly divided into training, validation, and test sets using a random number generator (SPSS Statistics version 26, IBM, Armonk, NY, USA). The 10 m and 17.5 m images were randomized independently of each other. A 70%-15%-15% ratio was used to ensure optimal set sizes. The outcome of the division is presented in **Table 1**. While the training and validation sets were used in the development of the algorithms, the test set was only introduced to the deep learning software at the final test round.

The open-source AIDeveloper software version 0.1.2 [17] was used for the deep learning procedure since it has multiple neural net architectures readily available for image classification. First, the processed images were uploaded to AIDeveloper in grayscale format at the size of 200 x 200 pixels. Secondly, a training and validation round of up to 2000 epochs was run for each architecture. **Supplementary Table 1** presents the specific parameters used in the training and validation process, and **Supplementary Table 2** lists the neural net architectures used. Thirdly, the best-performing algorithm was selected from each architecture, and these algorithms were then tested using the test set (**Supplementary Table 2**). In the Results section, we present the best-performing algorithm from the test set round.

The choice of the best-performing algorithm was made according to the following performance metrics: accuracy (true positives + true negatives)/total), precision (true positives/(true positives + false positives)), recall (true positives/(true positives + false negatives)), and F1 value (2 x (precision x recall)/(precision + recall)) [17, 18]. The best-performing algorithms are not published alongside the article as their wider applicability is likely to be low due to the small and select sample.

3. Results

In this dataset of 106 shotgun pattern images, a TinyResNet-based algorithm was able to distinguish between the 10 m and 17.5 m patterns with an accuracy of 94% (**Supplementary Table 2**). From the testing set, the algorithm classified all 10 m patterns correctly and misclassified one 17.5 m pattern (**Table 2**). The detailed performance metrics of this algorithm are presented in **Table 3**.

4. Discussion

This proof-of-concept study aimed to explore the potential of neural net architectures to classify shotgun pattern images correctly on the basis of shooting distance. In our preliminary dataset, a TinyResNet-based algorithm reached a relatively high testing accuracy of 94%, warranting further research into the forensic applications of deep learning in shotgun patterning.

As the interpretation of gunshot patterns may be complicated by wide range of confounding factors, universally applicable generic methods to reliably estimate shooting distance are yet to be developed. Although it is well known that shotgun patterns enable higher potential for shooting distance estimation than firearms causing individual wounds (e.g. [7, 19]), the role of shotgun patterning in forensic shooting distance estimation could be improved considerably. Importantly, the high accuracy reached by the best-performing algorithms of this preliminary study clearly demonstrated the potential of deep learning to aid in the shooting distance estimation process.

Our study has several strengths. The main strengths were the simplicity of our experimental setting and the obtained, encouraging results. Due to the preliminary nature of our study, we decided to place full focus on shooting distance and successfully minimized the potential external and circumstantial confounding factors. Although our setting utilized a relatively minor, namely 7.5-meter difference between the two shooting distances, the classification accuracy of the best-performing algorithm was surprisingly high.

There are inevitable limitations in our study. Importantly, the external applicability of our study as such is obviously limited. Shotgun patterning is a very complex issue and in summary patterning is very much ammunition and barrel specific (e.g. [7, 9]). As we only used one choke, shell and pellet type, our results only cut into the potential to separate the shooting distances of 10 and 17.5 meters from each other. Our dataset was comprised of only 106 images, which is a greatly limited dataset size for deep learning procedures. However, this study provided a clear positive indication that with larger and more robust sets of data, deep learning approaches could potentially provide a beneficial tool for more effective forensic shotgun pattern interpretation.

Our preliminary results are only the first steps into the development of robust tools in shotgun pattern interpretation. In the future, studies are encouraged to build on substantial data pools of preferably real-world images and large-scale pattern testing when developing algorithms for potential forensic and judicial use. Importantly, shooting distance should be modelled continuously rather than in discrete categories, and obviously the variation of choke, shell and pellet should be carefully considered. To expedite data collection processes and increase coverage in terms of weapon-ammunition-distance combinations, multicenter collaborations might prove fruitful. With these remarks, it is expected that robust and generalizable algorithms will eventually serve as a beneficial tool for forensic investigators, expediting or even improving the accuracy of forensic shotgun pattern interpretation. In particular, we expect the tools to prove helpful in scenarios with very little background information available.

In this proof-of-concept study, a deep learning based algorithm classified shotgun pattern images on the basis of two shooting distance categories at an accuracy of 94%. It thus seems achievable to develop algorithms that would serve as a beneficial tool for forensic investigators when estimating shooting distances from shotgun patterns. In the future, additional studies with larger datasets (addressing also the choice of choke, shell and pellet) are encouraged to develop more robust and universally applicable algorithms in shotgun pattern interpretation.

Reference list

1. Wolfson JA, Teret SP, Frattaroli S, et al (2016) The US Public's Preference for Safer Guns. Am. J. Public Health 106:411–413
2. Karp A (2018) Estimating Global Civilian-held Firearms Numbers. Small Arms Survey, Geneva, Switzerland
3. Dolinak D, Matshes E, Lew EO (2005) Forensic Pathology: Principles and Practice 1st Edition. Academic Press, Burlington
4. Denton JS, Segovia A, Filkins JA (2006) Practical pathology of gunshot wounds. Arch Pathol Lab Med 130:1283–1289. https://doi.org/10.1043/1543-2165(2006)130[1283:PPOGW]2.0.CO;2
5. Knight B, Saukko PJ (2004) Knight's Forensic Pathology Fourth Edition. Hodder Arnold, London
6. Junno J-A, Junno A, Oura P Deep learning in forensic gunshot wound interpretation - A proof-of-concept study. Int J Legal Med
7. Breitenecker R (1969) Shotgun wound patterns. Am J Clin Pathol 52:258–269. https://doi.org/10.1093/ajcp/52.3.258
8. Ordog GJ, Wasserberger J, Balasubramaniam S (1988) Shotgun wound ballistics. J Trauma 28:624–631. https://doi.org/10.1097/00005373-198805000-00011
9. Wilson JM (1978) Shotgun ballistics and shotgun injuries. West J Med 129:149–155
10. Bolton P (1901) Multiple birdshot wounds. Ann Surg 34:419
11. Moreau TS, Nickels ML, Wray JL, et al (1985) Pellet Patterns Fired by Sawed-Off Shotguns. J forensic Sci 30:137–149
12. Maitre M, Chiaravalle A, Horder M, et al (2021) Evaluating the effect of barrel length on pellet distribution patterns of sawn-off shotguns. Forensic Sci Int 320:110685. https://doi.org/10.1016/j.forsciint.2021.110685
13. Rowe WF, Hanson SR (1985) Range-of-fire estimates from regression analysis applied to the spreads of shotgun pellet patterns: Results of a blind study. Forensic Sci Int 28:239–250. https://doi.org/https://doi.org/10.1016/0379-0738(85)90134-3
14. Flint LM, Cryer HM, Howard DA, Richardson JD (1984) Approaches to the management of shotgun injuries. J Trauma 24:415–419. https://doi.org/10.1097/00005373-198405000-00008
15. LeCun Y, Bengio Y, Hinton G (2015) Deep learning. Nature 521:436–444. https://doi.org/10.1038/nature14539
16. Hosny A, Parmar C, Quackenbush J, et al (2018) Artificial intelligence in radiology. Nat Rev Cancer 18:500–510. https://doi.org/10.1038/s41568-018-0016-5
17. Kräter M, Abuhattum S, Soteriou D, et al (2021) AIDeveloper: Deep Learning Image Classification in Life Science and Beyond. Adv Sci n/a:2003743. https://doi.org/https://doi.org/10.1002/advs.202003743
18. Machin D, Campbell M, Walters S (2007) Medical Statistics, Fourth Edition - A Textbook for the Health Sciences. John Wiley & Sons, Ltd, Hoboken, NJ, USA
19. Alfonsi A, Calatri S, Cerioni E, Luchi P (1984) Shooting distance estimation for shots fired by a shotgun loaded with buckshot cartridges. Forensic Sci Int 25:83–91. https://doi.org/https://doi.org/10.1016/0379-0738(84)90017-3

Tables

Table 1. Training, validation and test sets.

	Training set	Validation set	Test set
Size (% of total)	74/106 (69.8%)	16/106 (15.1%)	16/106 (15.1%)
Class 1 (10 m)	38	8	8
Class 2 (17.5 m)	36	8	8

Table 2. True and predicted classes on test set data according to the best-performing algorithm.

	Predicted class	
	Class 1 (10 m)	Class 2 (17.5 m)
True class		
Class 1 (10 m)	**100.0% (8/8)**	0.0% (0/8)
Class 2 (17.5 m)	12.5% (1/8)	**87.5% (7/8)**

Table 3. Performance metrics of the best-performing algorithm on test set data.

Metric	Class 1 (10 m)	Class 2 (17.5 m)
Testing accuracy	0.94	0.94
F1	0.94	0.93
Precision	0.89	1.00
Recall	1.00	0.88

Supplementary Tables

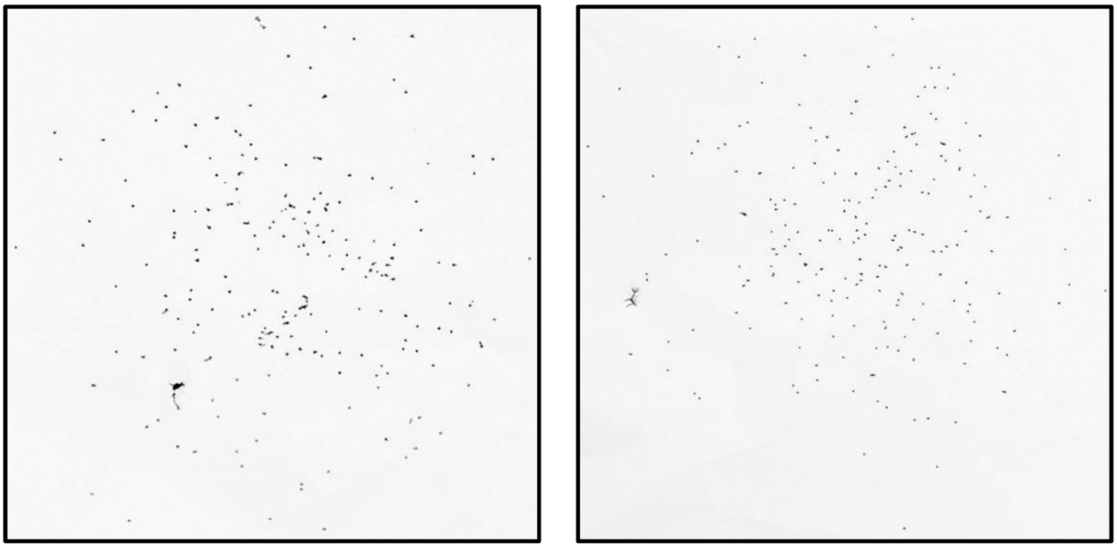
Supplementary Table 1. Parameters used in AIDeveloper.

Parameter	Value
Network architecture	Please find list in **Supplementary Table 2**.
Input image size (pixels)	200 x 200
Image normalization	Division by 255
Color mode	Grayscale
Padding	No
Total number of epochs for each architecture	2000
Image augmentation	Not used

Supplementary Table 2. Performance metrics of the explored neural network models.

Network architecture	Training and validation set			Testing set	
	Best epoch	Training accuracy	Validation accuracy	Testing accuracy	Correct per class (%)
TinyResNet	**1036**	**0.99**	**1.00**	**0.94**	**100.0/87.5**
CNN_4conv2dense_optim	142	1.00	1.00	0.88	87.5/87.5
LeNet5_bn_do	28	1.00	1.00	0.88	75.0/100.0
LeNet5_bn_do_skipcon	184	1.00	1.00	0.88	87.5/87.5
VGG_small_4	46	1.00	1.00	0.88	75.0/100.0
MhNet1_bn_do_skipcon	61	1.00	1.00	0.81	62.5/100.0
MLP_64_80_32	634	1.00	0.94	0.81	75.0/87.5
Nitta_et_al_6layer	36	0.92	0.94	0.81	62.5/100.0
VGG_small_1	127	1.00	1.00	0.81	75.0/87.5
LeNet5	41	1.00	1.00	0.75	50.0/100.0
MhNet2_bn_do_skipcon	26	1.00	0.94	0.63	37.5/87.5
LeNet_do	1024	0.99	0.81	0.56	50.0/62.5
MLP_4_4_4	0	0.59	0.50	0.50	100.0/0.0
MLP_8_8_8	1	0.53	0.50	0.50	100.0/0.0
MLP_16_8_16	0	0.43	0.50	0.50	100.0/0.0
MLP_24_16_24	0	0.53	0.50	0.50	100.0/0.0
MLP_64_32_16	0	0.53	0.50	0.50	0.0/100.0
MLP_72_80_32	0	0.53	0.50	0.50	0.0/100.0
MLP_72_48_24_32	0	0.54	0.50	0.50	0.0/100.0
MLP_72_64_48_48	230	0.85	0.63	0.50	0.0/100.0
MLP_24_16_24_skipcon	0	0.54	0.50	0.50	0.0/100.0
MLP_256_128_64_do	6	0.53	0.50	0.50	0.0/100.0
Nitta_et_al_8layer	184	0.99	1.00	0.50	25.0/75.0
Nitta_et_al_6layer_linact	62	0.59	0.50	0.50	100.0/0.0
Nitta_et_al_6layer_reluact	0	0.54	0.50	0.50	100.0/0.0
TinyCNN	90	0.51	0.50	0.50	100.0/0.0
VGG_small_2	-	-	-	-	-
VGG_small_3	-	-	-	-	-

Figures



10 m **17.5 m**

Figure 1. Representative examples of shotgun patterns from two distances (10 m and 17.5 m).