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A multi-factor knuckle and nail bed verification tool for forensic imagery analysis

Abstract

Background: The grooming process involves sexually explicit images or videos sent by the offender to the minor. Although offenders may try to conceal their identity, these sexts often include hand, knuckle, and nail bed imagery.

Objective: We present a novel biometric hand verification tool designed to identify online child sexual exploitation offenders from images or videos based on biometric/forensic features extracted from hand regions. The system can match and authenticate hand component imagery against a constrained custody suite reference of a known subject by employing advanced image processing and machine learning techniques.

Data: We conducted experiments on two hand datasets: Purdue University and Hong Kong. In particular, the Purdue dataset collected for this study allowed us to evaluate the system performance on various parameters, with specific emphasis on camera distance and orientation.

Methods: To explore the performance and reliability of the biometric verification models, we considered several parameters, including hand orientation, distance from the camera, single or multiple fingers, architecture of the models, and performance loss functions.

Results: Results showed the best performance for pictures sampled from the same database and with the same image capture conditions.

Conclusion: The authors conclude the biometric hand verification tool offers a robust solution that will operationally impact law enforcement by allowing agencies to investigate and identify online child sexual exploitation offenders more effectively. We highlight the strength of the system and the current limitations.

Keywords: online child sexual exploitation, knuckles, hands, biometric identification, forensic investigative tool

Introduction

Online child sexual abuse and exploitation continue to be a serious epidemic worldwide (Europol, 2023; WeProtect Global Alliance, 2023). Online child sexual abuse and exploitation includes a wide range of both contact and noncontact sexual behaviors that may occur in person and/or through technology (ECPAT, 2016). Since the COVID-19 pandemic, the National Center for Missing and Exploited Children (NCMEC; 2022a) continues to report a significant increase in the number of cyber tips related to child sexual exploitation and online enticement. Over 144 million reports of suspected child sexual exploitation have been made to the CyberTipline between 1998 and 2022 (NCMEC, 2022a); 32 million reports were made in 2022 alone, a 9% increase from 2021 (NCMEC, 2022b). Nearly all the reports received by the CyberTipline in 2022 were incidents of suspected child sexual abuse material (CSAM). NCMEC (2022b) also reported an 82% increase in online enticement reports from 2021 to 2022.

Online enticement occurs when an individual communicates with a child (or a person they believe to be a child) online with the intent to commit a sexual offense or abduction. Online enticement is "a broad category of online exploitation, including sextortion, in which a child is being groomed to take sexually explicit images and/or ultimately meet face-to-face with someone for sexual purposes, or to engage in a sexual conversation online or, in some instances, to sell/trade the child's sexual images" (NCMEC, 2022c). These different online offenses almost always involve chats between minors and offenders, and in these chats, the offenders engage in child sexual grooming.

Child sexual grooming is the process by which an adult uses deceptive trust and friendship formation to lure a minor into engaging in sexual behaviors (Gillespie, 2004). The grooming process involves sexually explicit images or videos sent by the offender to the minor

(International Centre for Missing & Exploited Children, 2017; Chancellor, 2021; Peters, 2022; Ringenberg et al., 2022). The offender sends pornographic sexts of their genitalia (e.g., imagery of themselves masturbating) or CSAM to groom the child that sexual behaviors between adults and minors are normal and "okay" (Chancellor, 2021; Feather, 1999; Lanning, 1992; Peters, 2022; Ringenberg et al., 2022). Although offenders try to conceal their identity (e.g., face or tattoos; Benson, 2017), images of the suspect's hand are often present and in more significant quantities for biometric analysis (Baines, 2011).

Consistent with other reports (Black, Mallett, Rynn, & Duffield, 2009; Blaines, 2011; Dan, Hackman, Rinaldi, & Trucco, 2023; Hackman & Black, 2023; Ring, 2016), our preliminary findings from child sexual abuse and exploitation cases examined at the Tippecanoe High Tech Crime Unit and Internet Crimes Against Children (ICAC) investigations revealed that the most common digital evidence of offender biometrics shared was of their hands (Seigfried-Spellar, 2020; 2021). Digital evidence is information either transferred or stored via a computer (Casey, 2011), and biometrics is the automatic identification of individuals based on behavioral or biological characteristics (Pato & Millett, 2010). Offenders exposed potential digital evidence in the form of knuckle and fingernail bed biometrics in pornographic sexts sent to minors (see Figure 1). In addition, these features were also present in the CSAM produced by child sex offenders (see case published by Planells Garcés, 2022).

Thus, the current study examined the potential for knuckle and fingernail bed biometrics to be a critical form of digital evidence in online child sexual abuse and exploitation cases. For our experiments, we relied on two hand datasets with different demographic and collection criteria. We describe the algorithms and software used for identifying hands and cropping the region of interest; the pre-processing of the extracted region of interest (RoI); the models used

for biometric verification; and the fusion criteria. The critical contribution of this study is a biometric hand verification tool that proposes a solution for law enforcement investigating child sexual exploitation cases.

Figure 1

A sanitized example of a sexually explicit image by an adult male depicting knuckle and fingernail bed biometrics



Note. Original image obtained from Wikimedia Commons.

State of the Art

Various biometric modalities for capturing and comparing physiological or behavioral characteristics have been explored for different application scenarios. For example, faces and fingerprints on mobile devices are widely deployed for verification or identification (Jain et al., 2004). Biometrics relating to the hand include fingerprint, dorsal vein pattern, hand geometry, and palm print (Pankanti et al., 2000), while fingerprints also have a rich history within the forensics community, providing legally admissible evidence for over a century (Garrett, 2018).

Pioneering studies on knuckle crease biometrics were first published around 2007-2009 (Kumar & Ravikanth, 2009; Kumar & Zhou, 2009; Ravikanth & Kumar, 2007). These studies

utilized conventional image processing techniques, such as linear filters translated into subject-specific encodings on constrained imagery. Importantly, they proved the validity of knuckle creases within an automated biometric verification context. A non-automated method for marking up and interpreting critical features of knuckle creases, specifically for forensic use, was developed in 2011 (Baines, 2011). The work included a framework for matching marked-up knuckle pairs for legal presentation of evidence. More recently, research has shown the validity of fingernail beds as another form of unique biometrics for human identification (Garg & Kumar, 2012; Heidari & Chalechale, 2022; Kumar, Garg, & Hanmandlu, 2014). Fingernail beds are also visible and processible, so the hand provides a unique opportunity to verify a suspect's identity through a multimodal approach incorporating several biometric features from a single image or video (Aftab et al., 2021).

Two key factors drive the increased use of knuckle crease imagery for biometric assessment – first, the visibility of the knuckle ridge pattern (Baines, 2011). In a criminal forensic context, a person might go to great lengths to conceal aspects of their identity regarding their face or body modification (e.g., tattoos). However, images containing the back of a subject's hand are often obtainable in greater quantities (Blaines, 2011). The second driver is the increased resolution quality of standard cameras on mobile devices and (semi-)professional photographic equipment (Baines, 2011). Thus, the level of detail related to knuckle creases is visible and processible even when the region of interest is small within an overall image.

Knuckles have several other advantages, including high permanence, contactless donation (i.e., touchless, meaning no physical contact is made between the individual and biometric device), uniqueness, and universality (see Aftab et al., 2021). These advantages are balanced against finger rotational issues concerning the camera when used in an unconstrained

setting and finger flexion, modifying an identification pattern by the tightening or loosening of the skin (De-Santos-Sierra et al., 2011). Automated techniques must be robust to these issues in any solution. Biometric performance will also be affected by image quality, illumination, camera equipment, and distance between the source hand and the camera (Arya & Bhadoria, 2019).

A conventional implementation can be conceptualized as containing five main stages (Usha & Ezhilarasan, 2015): 1) Image capture; 2) Knuckle region of interest identification and extraction; 3) Image processing – such as image skew correction, contrast enhancement, and binarization; 4) Feature extraction; and 5) Comparison (using two or more images). While region of interest identification may be automated or manual, research and development work has primarily focused on the feature extraction and comparison stages. As outlined in Jaswal et al. (2016), feature extraction can be broadly grouped into three categories: 1) subspace (typically a filtering operation followed by principal component analysis/linear discriminant analysis) coefficient assessment using the raw image as an input (Microsoft, n.d.; Attia et al., 2021); 2) knuckle texture assessment (Kong et al., 2014; Choras & Kozik, 2010); and 3) image processing and encoding methods (e.g., steerable orientation coding) for description of knuckle contents such as edges/ridges (Gao et al., 2014; Kumar & Zhou, 2009). Across all techniques, rotational and illumination invariance is critical to ensure that performance is not affected by finger and camera position or lighting/shadow effects.

Various techniques compare image features from traditional distance metrics (e.g., Hamming, Euclidean) to trained classifiers such as Support Vector Machines (SVMs) and Hidden Markov Modelling (HMMs). Recent work has also utilized deep learning-based topologies for image comparison (Chlaoua et al., 2019) and three-dimensional knuckle patterns (Cheng & Kumar, 2019). System performances are high, with error rates typically between 1 and

2%. While these levels illustrate deployable systems, test images are usually drawn from constrained sources (e.g., the Poly U Contactless Finger Knuckle Images Database) with consistent lighting, camera distance, and finger positioning (Kumar & Xu, 2016). Although these databases provide valuable resources, operationally, these fingers only represent captures within environments such as police custody suites.

A typical scenario facing forensic examination occurs when a knuckle image taken "in the wild" (i.e., from an image with unconstrained lighting, positioning, and distance) is compared against a constrained image (e.g., exemplar known image). From this perspective, previous studies and databases do not provide a realistic representation of a real-life forensic scenario, as these images are captured in ideal conditions and camera angles, good lighting, a clear view of the hand, high resolution, and no blurriness or distortion. In our study, we addressed these issues through a semi-constrained dataset and explored biometric performance in relation to different parameters, such as camera distance and angle.

Methods

Datasets

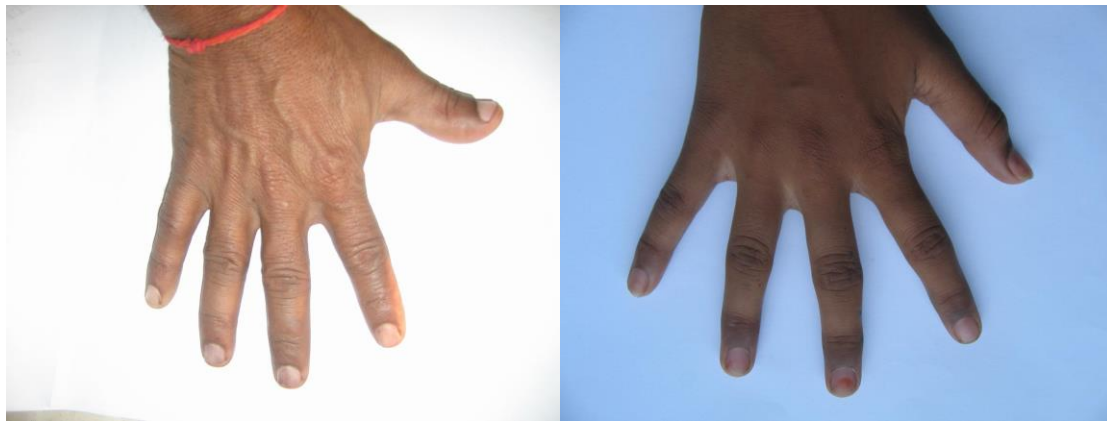
In our study, we conducted experiments on two hand datasets collected from various institutions with differing protocols and sample demographics: the Hong Kong dataset (Kumar & Xu, 2016) and the Purdue University dataset collected for this study. We describe the composition of these datasets below.

Hong Kong Dataset: Officially known as the Hong Kong Polytechnic University Contactless Hand Dorsal Images Database (Kumar & Xu, 2016), images were collected from three locations (i.e., IIT Delhi campus, Hong Kong Polytechnic campus, and rural villages in India) across multiple years between 2006 and 2015. The dataset comprised 2505 hand dorsal

images from the right hand of 501 different subjects. All the pictures were taken from the same distance and angle of the hand, with no pose variation and controlled lighting (see Figure 2). This database also provided hand dorsal images from two sessions, with many samples in different age groups acquired after a long interval (4 to 8 years) to support studies relating to the stability of knuckle patterns.

Figure 2

Two pictures from different users in the Hong Kong Database.



Purdue University Dataset. The Purdue dataset was smaller in terms of the amount of data and variability in sample demographics; however, it introduces other important semi-constrained variables that make it descriptive of a real-life scenario. In 2021, we completed knuckle data collection on seven subjects in a controlled environment to assess different elevation conditions and controlled angle conditions within specific ranges (IRB# 2021-369). Each subject would place their hand in the designated capture area underneath the mobile/cell smartphone camera. For enrollment, each hand was captured five times on the smartphone at an angle of 0° .

After enrollment, the camera angle was adjusted to 45° , 22.5° , 0° , -22.5° , and -45° . At each angle, five images were captured from each hand. Once all images were captured at each angle, five images were captured at three elevation levels: 20 cm, 50 cm, and 100 cm. The entire process was repeated for a digital single-lens reflex (DSLR) camera. A capture sequence is shown below in Table 1. Figure 3 shows three images taken using a DSLR at 0° , 22.5° , and 45° with the cropped middle finger knuckle region from each shown below.

Table 1

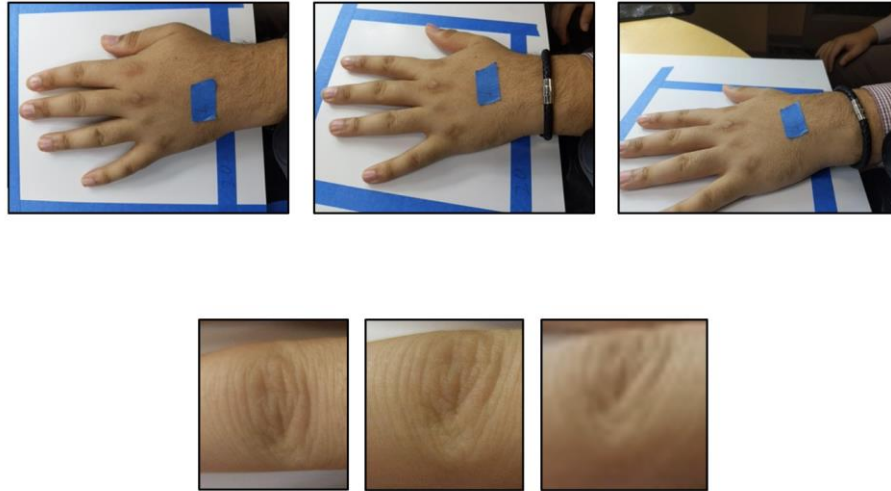
Purdue University Dataset Camera Azimuth and Elevation

Sequence Set	Azimuth (Degrees)	Elevation per set (cm)
Smartphone		
1	45	20
2	22.5	
3	0	
4	-22.5	
5	-45	
6	45	50
7	22.5	
8	0	
9	-22.5	
10	-45	
11	45	100
12	22.5	
13	0	
14	-22.5	
15	-45	
DSLR		
16	45	20
17	22.5	
18	0	
19	-22.5	
20	-45	
21	45	50
22	22.5	
23	0	
24	-22.5	
25	-45	
26	45	100
27	22.5	
28	0	
29	-22.5	
30	-45	

Note. Five images were captured per subject by a Smartphone and DSLR camera. The elevation reported was the same for each number in the sequence set.

Figure 3

Examples of whole hand and cropped middle finger images from Purdue University Dataset at three angles.



Design & Procedures

To automate the process of hand detection, we relied on MediaPipe (Google, n.d.), an artificial intelligence (AI)-powered Application Programming Interface (API) developed by Google for human body tracking on images and videos (information on the operation of the hand tracking element of MediaPipe can be found at the cited hand landmarks detection guide). The software can detect up to six hands in a frame with variable confidence levels depending on the selected model's complexity. The model returns the hand joints' estimated landmarks (with x, y, and z coordinates) for 21 landmarks per hand. The landmarks' coordinates in pixels refer to the frame coordinate system (origin in the top-left corner with the z-axis pointing away from the observer). Still, the z coordinate estimated the depth performed by MediaPipe itself.

This has several implications and limitations, such as: 1) Enumeration order of the found hands based on their detection order, starting from the top-left corner; 2) Possible overlapping

landmarks due to closed knuckle or partially obscured/hidden hand; 3) Non-normalized values; and 4) Non-oriented hands found. Some of these issues can be solved considering that MediaPipe also provides fixed numbering on the fingers' joints, starting from the thumb and ending with the pinkie.

Once the hand was correctly detected, the first two issues to address were 1) the location, shape, and size of the regions of interest and 2) the orientation of the region of interest (RoI) after the segmentation. In the case of the finger knuckle, it was easy to estimate its location since MediaPipe returns the coordinates of the joints. A rectangular/squared shape was determined to be the most optimal solution for two reasons: 1) ease of computation compared to more complex shapes that would better wrap the finger, and 2) the standard shape could easily be used as input to any pipeline (especially when working with convolutional neural networks, which in many cases require a fixed size rectangle-like shape). Moreover, a non-regular shape (or a spline) would most likely require padding and normalization, losing the initial benefits of tight cropping. For these reasons, we opted for a rectangular shape with adaptive size depending on the calculated Euclidean distance between consecutive joints.

The second issue directly relates to the first: cropping an area considering just the center positioning and the size of the sides. This, while ignoring the orientation of the fingers, would result in the extraction from the database of most unrelated images with additional noise generated from the randomness of the ridge lines from the knuckle. In addition, it would cause a significant impediment during the feature extraction process when using any sort of black box algorithms or topological techniques.

To solve this issue, before applying the cropping box to the selected finger, we calculated the orientation vector starting from the i -th joint of the considered finger knuckle (corresponding

to the center of the box) to the next joint (i -th +1) enumerated by MediaPipe. Next, considering the y versor of the box located at the joint coordinates and parallel to the image coordinate system, we calculated the rotational angle θ in degrees for the transformation with the 2-argument arctangent of the y and x coordinates of the finger orientation vector. Lastly, after converting the value from radians to degrees, we applied the linear transformation to the cropping box vertexes, defined as four couples of x and y coordinates, to get the new rotated vertex coordinates new_x , new_y (see Equation 1).

$$\theta = \arctg \left(\frac{y_{(center,i+1)} - y_{(center,i)}}{x_{(center,i+1)} - x_{(center,i)}} \right)$$

$$\begin{bmatrix} new_x(vertex) \\ new_y(vertex) \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x(vertex) \\ y(vertex) \end{bmatrix} \quad (\text{eq 1})$$

In our experiments, we first explored hand detection and RoI cropping performances. Then, we moved to image processing, feature extraction, and training of models for biometric verification. Specifically, we wanted to assess hand detection in real-life scenarios and pictures focused on the subject's hands. For this reason, we ran our software (composed of scripts to detect and process the RoI, incorporating functions from MediaPipe) on the Purdue dataset. We calculated the percentage of detected hands (or sensitivity) and the percentage of successful cropping of the RoI. However, we did not consider specificity due to the absence of pictures with no hand. Once the RoI was extracted, oriented, and resized, we converted it to grayscale and directly passed the new input image to the models we trained.

We trained two neural networks as feature extractors to perform the biometric verification. Each architecture has advantages and disadvantages; the underlying idea was not to

blindly try different models until the optimum was found but to acknowledge the variations across the data-capturing processes from different sources. More specifically, we wanted to provide situational models since a single model could not completely generalize across all the possible variables (e.g., demographic, camera angle, recording conditions).

We implemented ResNet (He et al., 2016) and VGG-16 (Simonyan & Zisserman, 2015) for their specific properties. Visual Geometry Group (VGG) performs well in terms of geometry and texture features. At the same time, a Residual Network (ResNet) with residual layers can be used when comparing samples that share standard features (e.g., skin tone) while focusing on specific topographic features. We trained the models on the Hong Kong Database, which was the largest but more constrained compared to the Purdue dataset and with one demographic. We repeated the training for both knuckle prints and nail beds. Once we reached an error rate below 10%, we tested the models on the Purdue dataset to evaluate their performance in more realistic scenarios and with different parameters (camera distance, rotation angle, fingers).

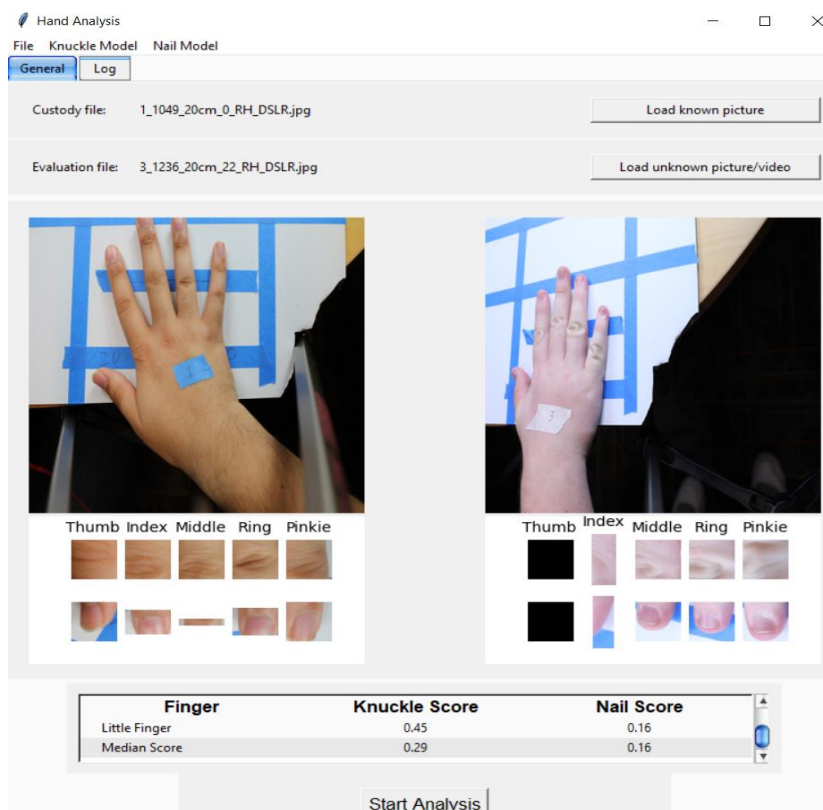
During the training stage, we explored two loss functions: the cross-entropy loss (imitating an identification task) and a triplet loss (to maximize distances between embeddings). In the first case, the fully connected layer before the logits layer was selected as embeddings output after the training. In the second case, the last layer with the embeddings for the triplet loss was selected as output. We performed the biometric verification tests comparing the embeddings of a template picture versus the embeddings of each sample picture, using the Euclidean distance as the metric. The Euclidean distance between the two images is calculated by summing up the squared differences of all the embeddings and then calculating the square root of the result. This is conceptually the same metric used in the triplet loss function during the training process, making it the optimal distance metric for the proposed algorithm. All embeddings were L2-

normalized. After training the single models for knuckle and nail beds, we developed a fusion model with a merging layer that combined the outputs of the previous two models and a one-dimensional vector with 256 embeddings as output. This last model could only work on paired images. For this reason, we could not provide an extensive evaluation of all the parameters mentioned above due to a lack of pairs.

As the last step, we developed a graphical user interface (GUI) application (see Figure 4) to perform all the tasks (except the active training of the models).

Figure 4

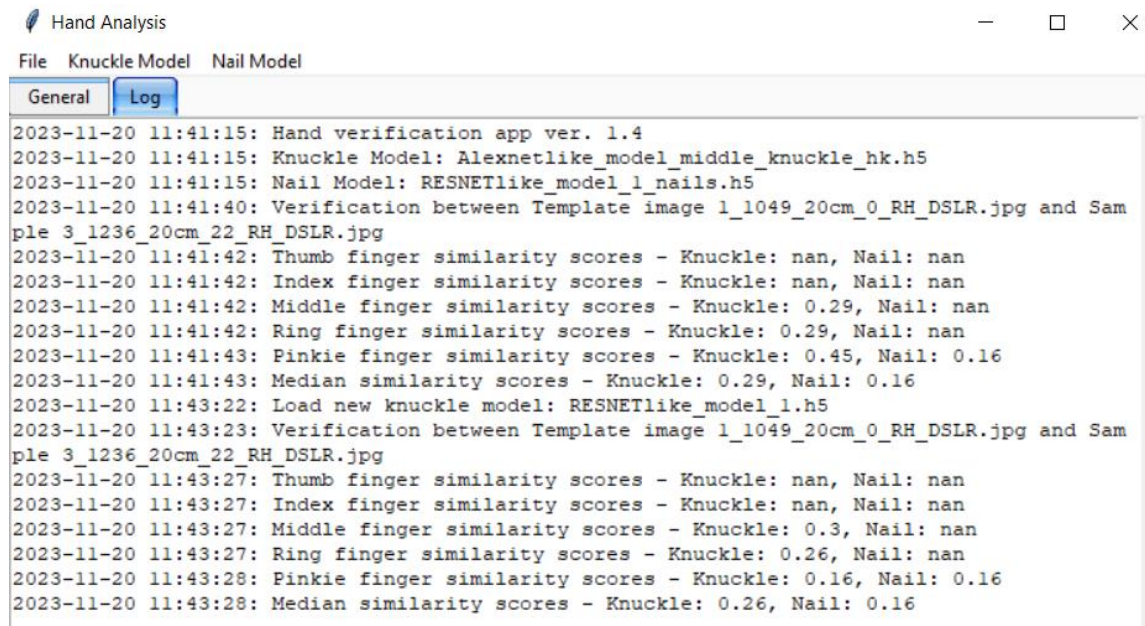
The main screen of the app has options to load two pictures/video, load different biometric models, and run the evaluation.



The app can load pictures or videos on request, automatically detect hands, and extract the related RoI for knuckle and nail beds. In cases involving a video, the best frame will be selected in terms of confidence of the detected hand and coplanarity of the hand with the camera frame. When failure to detect a hand occurs, the user can manually indicate the hand's RoI in the picture. The user can select any pre-trained and stored verification models and run the evaluation. The app will return the similarity score for each knuckle and nail bed and provide an overall median value. Finally, the app log file stores all the user's actions and results (see Figure 5).

Figure 5

A screenshot of the app log. It records every action, including data loading and swapping of models.



Results

From our experiments, we could assess the consistency of the hand detection and the biometric verification performance under different recording circumstances. The hand detection

software, in general, could accurately spot the hands in the picture, even when partially covered (contextual information). Still, it struggled when the entire image was focused on the hand; that is to say, the hand was close to the camera with no extra elements. In the case of the Hong Kong Database, we achieved a detection rate of 100%. This result was likely due to the very constrained nature of the data.

For the Purdue University Dataset of combined pictures from the smartphone and DSLR, we obtained a detection rate of 97.35%. Most undetected hands corresponded to close-up pictures with tilted hands or when there lacked a complete visual of the hand. Table 2 shows the hand detection rates at various distances and angles.

Table 2

Detection accuracy relative to camera distance and angles for the Purdue University dataset.

Distance (cm)	Angles		
	0	22	45
20	97.09	97.03	93.99
50	99.64	99.73	99.36
100	95.34	97.61	98.89

Note. Values represent percentages. Angle performance reported for 0, -22.5/22.5, and -45/45 together.

After successful detection, our system estimated the orientation of the fingers and automatically performed the cropping around the knuckles with a square RoI, aligning the region vertically. We achieved a successful cropping rate of 99.74%, with a total of 7599 RoI extracted from the detected hands and five cropping failures.

We trained the biometric verification models separately on the Hong Kong Dataset and then tested them on the Purdue dataset. To generate genuine and imposter images, we encoded

each different subject and assigned that value to cropped images. We compared all the photos to the according finger- images from the same class were classified as genuine, and images from the different class were classified as imposter. Generalization was challenging, primarily due to different demographic and image-capturing conditions, especially considering the worst cases with a 45-degree angle and 100 cm distance. The thumb also generally provided the lowest accuracy in almost all scenarios due to the difficulty of having a clear view of the knuckle prints or the nail bed. In Figures 6-9, we present the results for all the models and all the conditions in ROC format. Several observations can be made from these results:

- 1) Accuracy increased for images taken nearer to the hand.
- 2) Nail bed verification performs similarly to knuckle imagery, with slightly better results in optimal conditions (no rotation, close to the camera).
- 3) The performance of individual hand elements is broadly similar; however, optimal selection can be made according to known camera distance and angle parameters.
- 4) Typically, the best performance for each figure element ranges from 19 - 30% EER for knuckles and 14 - 25 % EER for nail beds.

These error rates may guide a manual inspection following a computer assessment of image pairs. Further studies may involve the development of fusion algorithms to combine the two modalities, either at the feature level or embedding level.

Figure 6

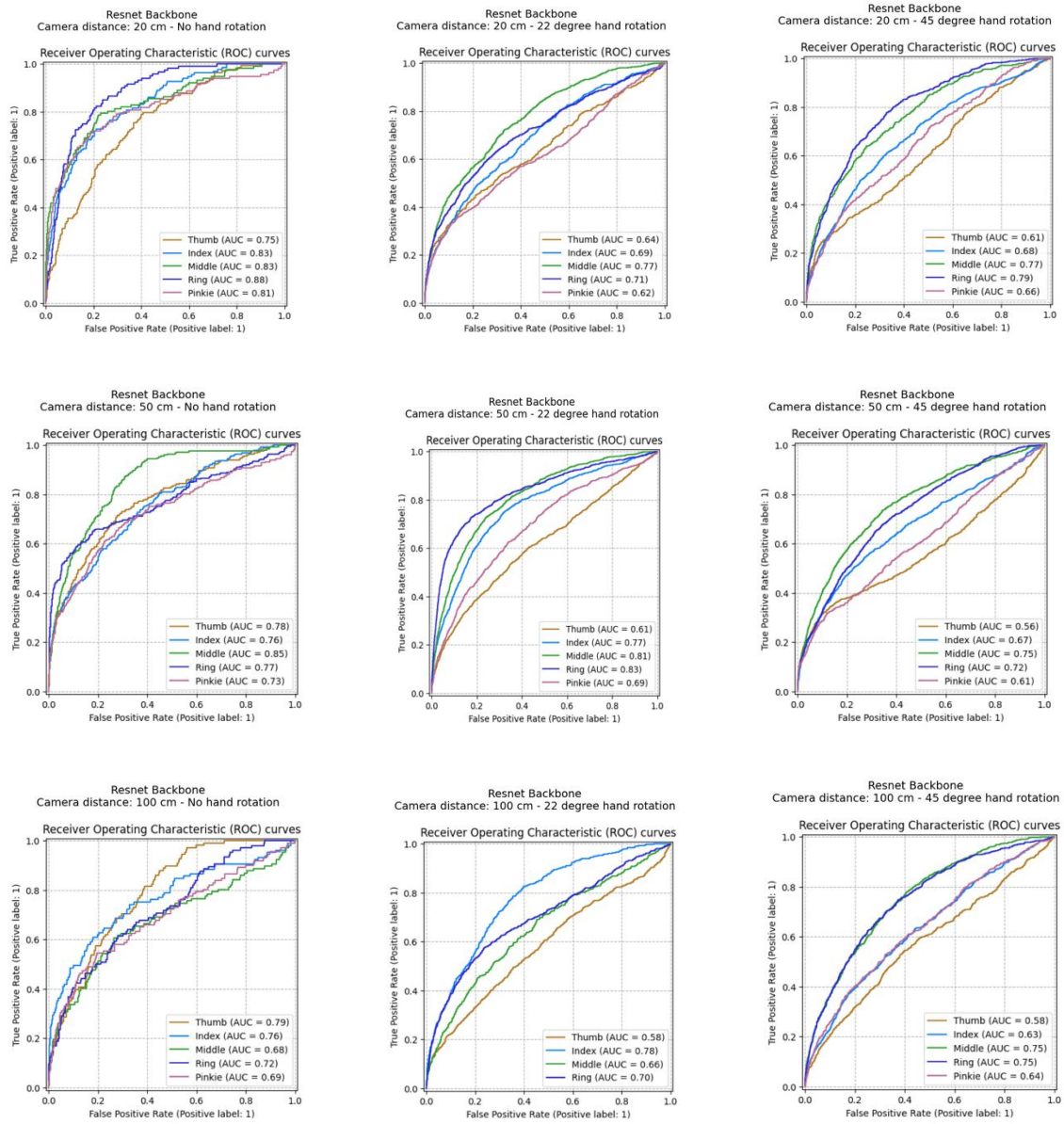
ResNet Knuckle Results

Figure 7

VGG Knuckle Results

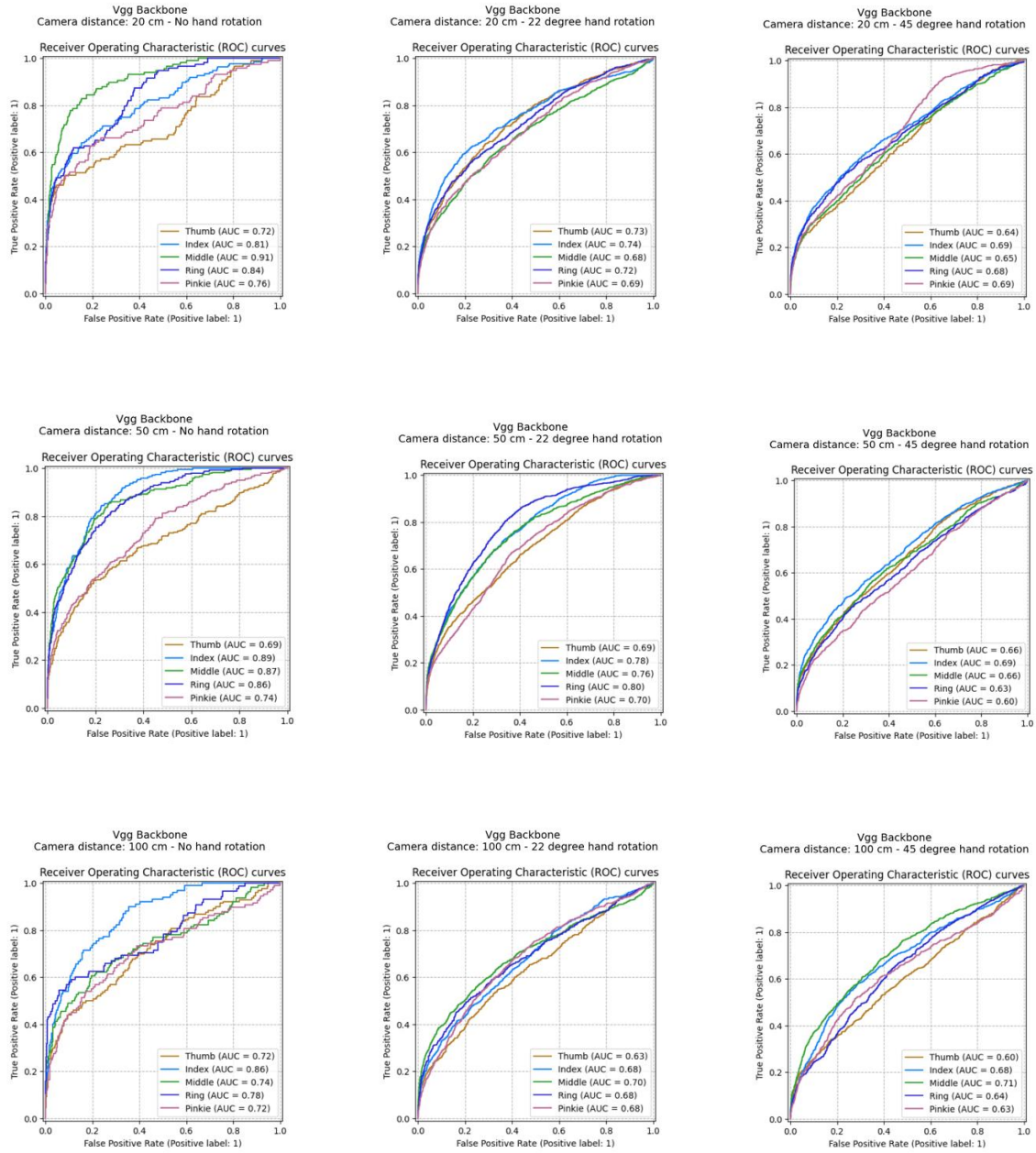


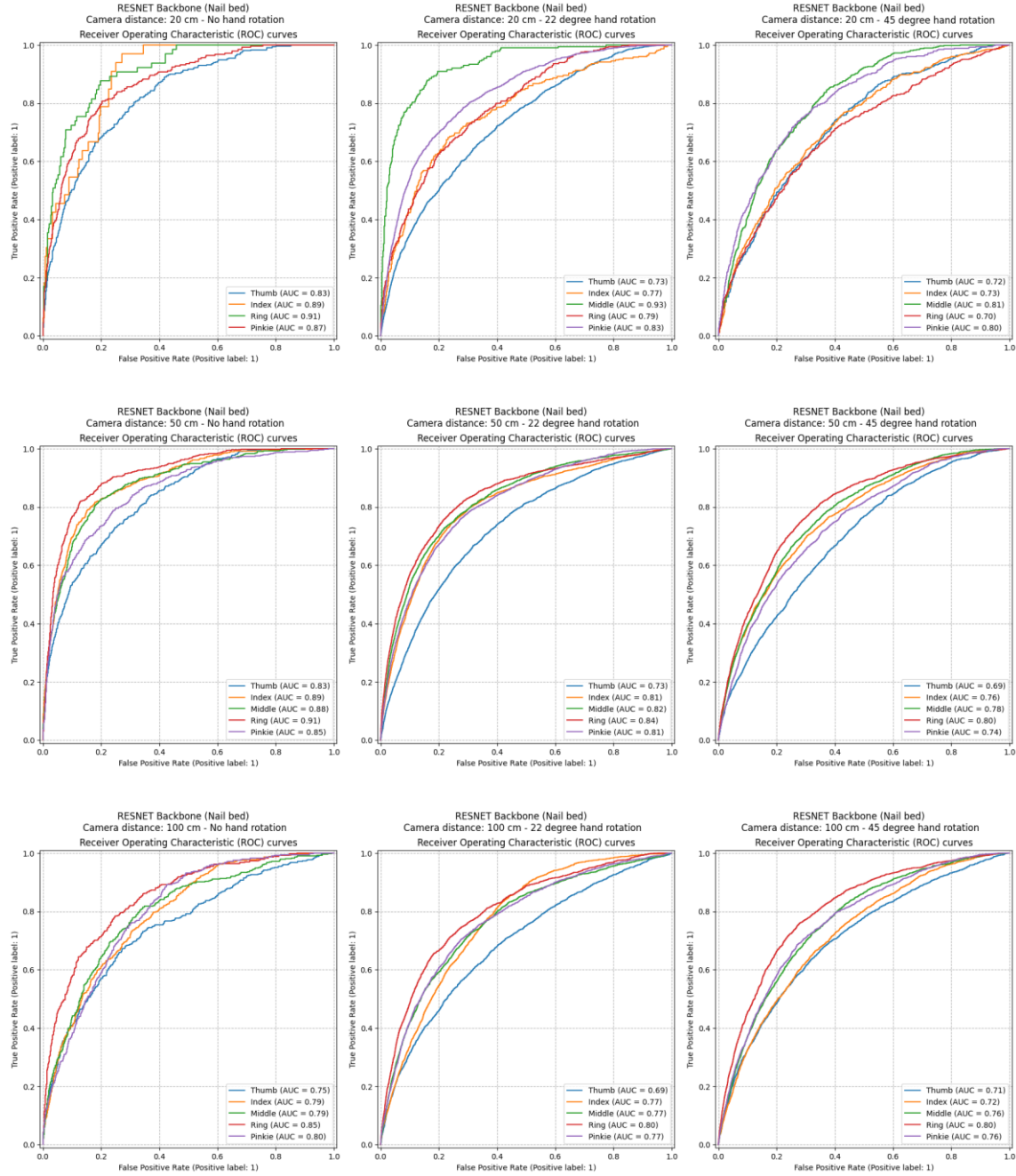
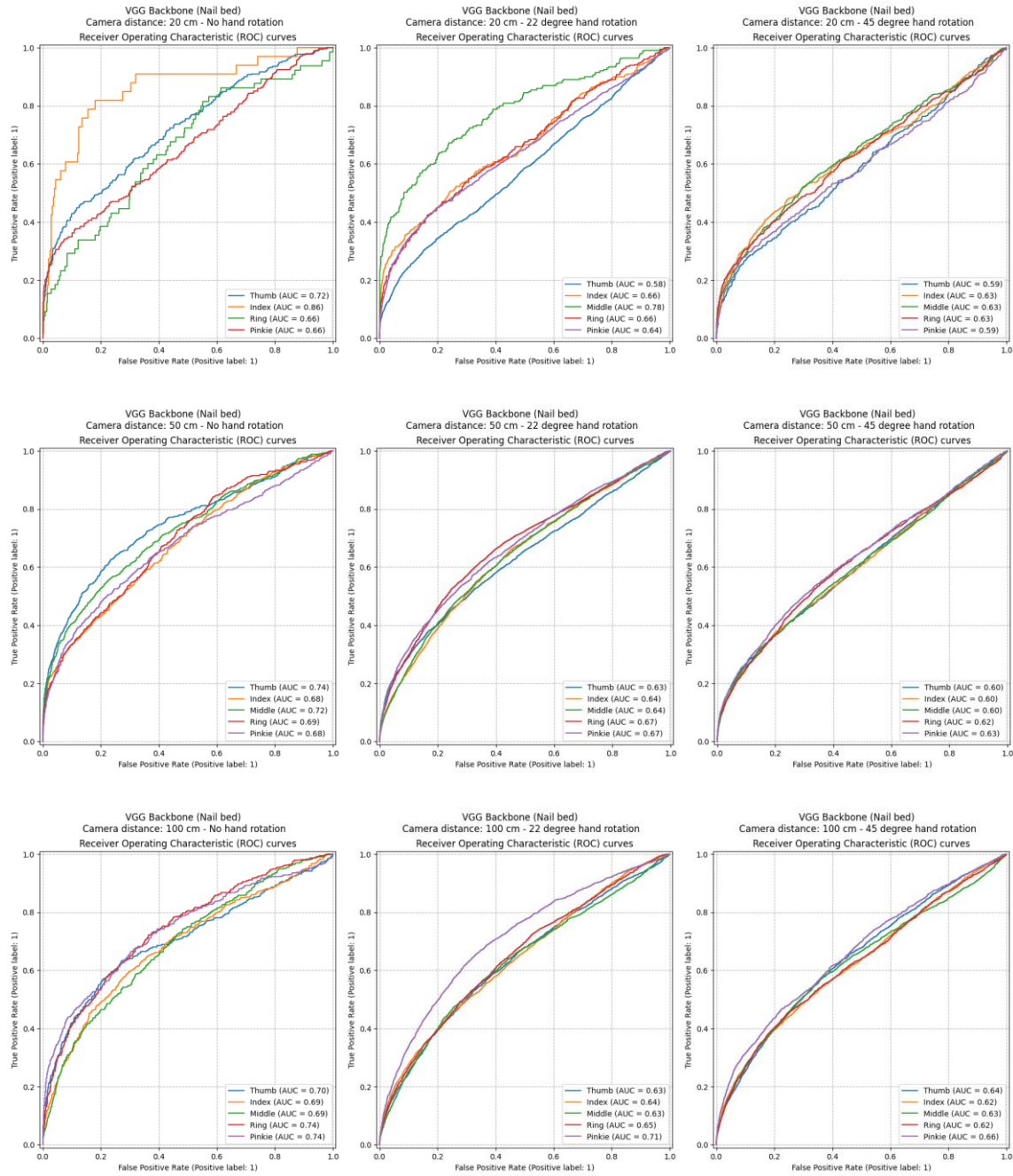
Figure 8*ResNet Fingernail Bed Results*

Figure 9*VGG Fingernail Bed Results*

Discussion

In the current study, we conducted a series of experiments showing that we can accurately detect and crop individual hand subcomponents within both constrained (such as those collected in a custody suite) and "in the wild" images. Notably, we have developed an automated image-based classifier for verifying *semi-constrained* hand images by studying varying distance, camera, and hand rotation. Our system has illustrated the development of a tool that may be used to guide an assessor on the match performance of individual hand components. Computer-based assessment scores may be confirmed through manual inspection, similar to the verification of fingerprints by a forensic expert (see Vanderkolk, 2012).

Preliminary testing and applications on data "in the wild" have shown that our tool is promising and likely to assist law enforcement with investigating cases of child sexual exploitation. In addition, we see future applications with other criminal investigations, as digital evidence is estimated to be a factor in about 90% of criminal cases (National Police Chiefs Council, July 2020). Digital and multimedia forensic examiners work on a variety of criminal cases other than online child sexual abuse and exploitation, such as burglary, school shootings, police-involved shootings, rape, fraud, and drug-related offenses (Clifford, 2011; Seigfried-Spellar, 2018).

Mobile phones are the most seized devices in criminal investigations (Fukami et al., 2021). The popularity of smartphones has also increased the ease of receiving and distributing high-quality multimedia (e.g., images/videos) via social media and native texting. Over 92% of all photos are taken on a smartphone, with the majority being selfies (Woolf, 2023). The average person has over 2,700 pictures on their smartphone (Peterson, 2023). Thus, images and videos will continue to be important forms of digital evidence in criminal cases, such as identity theft

(e.g., suspect holding a credit card), drug trafficking (e.g., suspect pinching a pill baggy), or homicide (e.g., suspect gripping a weapon).

A secondary benefit of developing automatic hand-based component detection and analysis is the reduction of exposure to CSAM by law enforcement and digital forensic examiners. Criminal justice professionals, including digital forensic examiners, are at an increased risk for experiencing vicarious trauma and work-related stress (Burruss, Holt, & Wall-Parker, 2017; Denk-Florea et al., 2020; Holt & Blevins, 2011; Holt et al., 2011; Kelty et al., 2021; Perez et al., 2010; Seigfried-Spellar, 2017). The ability to process CSAM images and videos quickly and identify frames with offender hand biometrics will reduce law enforcement's need to review CSAM frame by frame, thereby reducing exposure. We expect this technology will positively impact the psychological well-being of law enforcement investigating cases of child sexual abuse and exploitation.

Limitations and Future Research

The current limitations of the proposed software relate to the use of third-party freeware (MediaPipe) for the initial object detection task and to the system's error rates. It is possible to replace MediaPipe (using alternatives such as MMPose, OpenPose, Detectron2, and other open-source packages), but it would require the training of a dedicated algorithm. We recognize that technological improvements to third-party hand-tracking algorithms will positively impact our system's performance - the standalone role of these algorithms means that new detection methods can be easily inserted into our processing pipeline.

Future research includes further development of techniques to forensically identify human subjects from multiple components from hand images, replicating a forensic scenario of comparing constrained with "in the wild" imagery, and applying a quality-based threshold to

swap components in and out of a decision framework. Our goal is to develop algorithms that perform well on both constrained (i.e., exemplar custody image template) and unconstrained data to meet the investigative needs of law enforcement. There is also a need to develop best practice guidelines for custody suite images of hands taken during the booking process, including lighting conditions, height, and camera angle recommendations. In addition, future testing will need to be conducted on imagery "in the wild" representing law enforcement CSAM investigations. This final testing requires collaboration with agencies to test on law enforcement-sensitive data.

Conclusion

Digital evidence will continue to be a probative factor in most criminal cases thanks in part to the popularity of mobile phones. In these criminal investigations, images and videos can become important forms of digital evidence that may reveal a suspect's identity through biometrics. Although traditional biometric recognition techniques rely on face, iris, and fingerprints, they are often not applicable in many cases due to the angle or poor image quality to detect fingerprints or the offender obscuring their faces. Thus, alternative and innovative approaches are required to detect other suspect biometrics in multimedia. We argue that knuckle and fingernail bed biometrics may play an essential role in suspect identification in criminal investigations that involve imagery of the suspect's hands, especially for online child sexual abuse and exploitation cases. In addition, a tool that automatically analyzes imagery for suspect hand biometrics creates an opportunity to quickly triage and reduce law enforcement's exposure to disturbing media, including CSAM. However, in the end, this is only a tool, and manual verification by a forensic expert will always be required.

References

- Aftab, A., Khan, F. A., Khan, M. K., Abbas, H., Iqbal, Q., & Riaz, F. (2021). Hand-based multibiometric systems: State-of-the-art and future challenges. *PeerJ Computer Science*, 7, 1-47.
- Arya, K.V., & Bhadoria, R.S. (Eds.). (2019). *The biometric computing: Recognition and registration* (1st ed.). Chapman and Hall/CRC. <https://doi.org/10.1201/9781351013437>
- Attia, A., Akhtar, Z., & Chahir, Y. (2021). Feature-level fusion of major and minor dorsal finger knuckle patterns for person authentication. *Signal, Image and Video Processing*, 15(4), 851–859.
- Baines, K. N., (2011). *Dorsal knuckle crease pattern: Utility for forensic human identification*, Unpublished Master's Thesis, University of Dundee: UK.
- Benson, R. (2017). To catch a paedophile, you only need to look at their hands. *Wired*. Retrieved from <https://www.wired.co.uk/article/sue-black-forensics-hand-markings-paedophiles-rapists>
- Black, S. M., Mallett, X., Rynn, C., & Duffield, N. (2009). Forensic hand image comparison as an aid for paedophile investigations. *Police Professional*, 184, 21-24.
- Burruss, G. W., Holt, T. J., & Wall-Parker, A. (2017). The Hazards of Investigating Internet Crimes Against Children: Digital Evidence Handlers' Experiences with Vicarious Trauma and Coping Behaviors. *American Journal of Criminal Justice*, 43(3), 433–447. <https://doi.org/10.1007/s12103-017-9417-3>
- Casey, E. (2011). *Digital evidence and computer crime: Forensic science, computers, and the internet*. Academic press.
- Chancellor, A.S. (2021). Online Offenders (Chapter 9). In *Investigating Sexual Assault Cases*

- (pp. 153-169). 2nd Edition. CRC Press.
- Cheng, K. H., Kumar, A. (2019). Contactless biometric identification using 3D finger knuckle patterns. *IEEE transactions on pattern analysis and machine intelligence*, 42(8), 1868–1883.
- Chlaoua, R., Meraoumia, A., Aiadi, K.E., & Maarouf, K. (2019). Deep learning for finger-knuckle-print identification system based on PCANet and SVM classifier. *Evolving Systems*. 10. 261-272. 10.1007/s12530-018-9227-y.
- Choras, M. & Kozik, R. (2010). Knuckle Biometrics Based on Texture Features. *International Workshop on Emerging Techniques and Challenges for Hand-Based Biometrics*, 1-5. doi: 10.1109/ETCHB.2010.5559285.
- Clifford, R. D. (2011). *Cybercrime: The investigations, prosecution and defense of a computer-related crime* (3rd ed.). Durham, NC: Carolina Academic Press.
- Dan, L., Hackman, L., Rinaldi, V., & Trucco, E. (2023). The persistence of knuckle creases during finger flexion for the identification of perpetrators from digital images of their hands. *Forensic Science International*, 348, 111603.
- Denk-Florea, C., Gancz, B., Gomoiu, A., Ingram, M., Moreton, R., & Pollick, F. E. (2020). Understanding and supporting law enforcement professionals working with distressing material: Findings from a qualitative study. *PLOS ONE*, 15(11), e0242808.
- De-Santos-Sierra, A., Sánchez-Ávila, C., Del Pozo, G. B., & Guerra-Casanova, J. (2011). Unconstrained and contactless hand geometry biometrics. *Sensors*, 11, 10143-10164. <https://doi.org/10.3390/s111110143>
- ECPAT. (2016). *Terminology guidelines for the protection of children from sexual exploitation and sexual abuse*. ECPAT International: Luxembourg. Retrieved from

- <https://ecpat.org/wp-content/uploads/2021/05/Terminology-guidelines-396922-EN-1.pdf>
- Europol. (2023). *Internet organized crime threat assessment (IOCTA) 2023*. Publications Office of the European Union, Luxembourg. Retrieved from <https://www.europol.europa.eu/publication-events/main-reports/internet-organised-crime-assessment-iocta-2023#downloads>
- Feather, M. (1999). Internet and child victimization. Paper presented at the *Children and Crime: Victims and Offenders Conference convened by the Australian Institute of Criminology in Brisbane*, 17, 1-22.
- Fukami, A., Stoykova, R., & Geradts, Z. (2021). A new model for forensic data extraction from encrypted mobile devices. *Forensic Science International: Digital Investigation*, 38, 1-10.
- Gao, G., Yang, J., Qian, J., & Zhang, L. (2014). Integration of multiple orientation and texture information for finger-knuckle-print verification. *Neurocomputing*, 135, 180–191.
- Garg, S., Kumar, A., & Hanmandlu, M. (2012). Biometric authentication using finger nail plates. *Expert Systems with Applications: An International Journal*, 41(1), 497-502.
<https://doi.org/10.1109/ISDA.2012.6416588>
- Garg, S., Kumar, A., & Hanmandlu, M. (2012). Biometric authentication using finger nail surface, *12th International Conference on Intelligent Systems Design and Applications (ISDA)*, Kchi, India, pp. 497-502.
- Garrett, B. L. (2018). The reliable application of fingerprint evidence. *UCLA Law Review: Discourse*. Retrieved from <https://www.uclalawreview.org/reliable-application-of-fingerprint-evidence/>
- Gillespie, A. (2004). Grooming definitions and the law. *New Law Journal* 154 (7124), 586–587.

- Google. (n.d.). *Mediapipe*. Retrieved May 3, 2024 from https://developers.google.com/mediapipe/solutions/vision/hand_landmarker, accessed 2024.
- Hackman, L., & Black, S. (2023), Forensic examination of the hand. *Journal of the Royal Anthropological Institute*, 29, 116-131. <https://doi.org/10.1111/1467-9655.13999>
- He, K., Zhang, X., Ren, S., & Sun, J. (2016, June). *Deep Residual Learning for Image Recognition*. Proceedings of 2016 IEEE Conference on Computer Vision and Pattern Recognition. CVPR '16. *IEEE*, pp. 770–778.
- Heidari, H. & Chalechale, A. (2022). Biometric authentication using a deep learning approach based on different level fusion of finger knuckle print and fingernail, *Expert Systems with Applications*, 191, 1-11.
- Holt, T. J., & Blevins, K. R. (2011). Examining job stress and satisfaction among digital forensic examiners. *Journal of Contemporary Criminal Justice*, 27(2), 230–250. <https://doi.org/10.1177/1043986211405899>
- Holt, T. J., Blevins, K. R., & Burruss, G. W. (2011). Examining the stress, satisfaction, and experiences of computer crime examiners. *Journal of Crime & Justice*, 35(1), 35–52. <https://doi.org/10.1080/0735648x.2011.631401>
- International Centre for Missing & Exploited Children. (2017). *Online grooming of children for sexual purposes: Model legislation & global review*. Retrieved August 21, 2023 from www.icmec.org.
- Jain, A. K., Ross, A., & Prabhakar, S. (2004). An introduction to biometric recognition. *IEEE Transactions on circuits and systems for video technology*, 14(1), 4–20.
- Jaswal, G., Kaul, A., & Nath, R. (2016). Knuckle print biometrics and fusion schemes—overview,

- challenges, and solutions. *ACM Computing Surveys*, 49(2), 1–46.
- Kelty, S. F., McQueen, E. J., Pymont, C., & Green, N. (2021). Avoiding burnout at the digital forensics coalface: Targeted strategies for forensic agencies in the management of job-related stress. *Forensic Science International: Digital Investigation*, 38, 301127. <https://doi.org/10.1016/j.fsidi.2021.301127>
- Kong, T., Yang, G., & Yang, L. (2014). A hierarchical classification method for finger knuckle print recognition. *EURASIP Journal on Advances in Signal Processing*, 1–8.
- Krizhevsky, A., Sutskever, I., Hinton, G. E., 2012. ImageNet Classification with Deep Convolutional Neural Networks. In F. Pereira, C. J. C. Burges, L. Bottou, K. Q. Weinberger (Eds.), *Advances in Neural Information Processing Systems* (pp. 1097-1105). Curran Associates, Inc.
- Kumar, A. & Garg, S. (2014). Biometric authentication using finger nail plates. *Expert Systems with Applications*, 41(2), 373-386
- Kumar, A. & Xu, Z. (2016). Personal Identification Using Minor Knuckle Patterns from Palm Dorsal Surface. *IEEE Transactions on Information Forensics and Security* 11, 2338–2348.
- Kumar, A. & Zhou, Y. (2009). *Human identification using knucklecodes*. Proceedings of the 3rd International Conference on Biometrics: Theory, Applications, and Systems. *IEEE*, pp. 1–6.
- Lanning, K. V. (1992). *Child molesters: A behavioral analysis for law enforcement officers investigating cases of child sexual exploitation*. National Center for Missing & Exploited Children. Retrieved from <https://www.ojp.gov/pdffiles1/Digitization/149252NCJRS.pdf>
- Microsoft (n.d.). *PhotoDNA*. Retrieved September 2, 2022 from <https://www.microsoft.com/en->

us/ photodna.

National Center for Missing and Exploited Children. (2022a). *US Department of Justice CY 2022*

Report to the Committees on Appropriations: OJJDP CyberTipline Report. Retrieved

November 2, 2023 from <https://www.missingkids.org/cybertiplinedata#dojreport>.

National Center for Missing and Exploited Children. (2022b). *CyberTipline 2022 Report*.

Retrieved November 2, 2023 from <https://www.missingkids.org/cybertiplinedata>.

National Center for Missing and Exploited Children. (2022c). *The Issues: Online Enticement*.

Retrieved from November 2, 2023 from <https://www.missingkids.org/theissues/onlineenticement>.

National Police Chiefs Council. (July 2020). *Digital Forensic Science Strategy*. Retrieved March 10, 2024 from

<https://www.npcc.police.uk/Digital%20Forensic%20Science%20Strategy%202020.pdf>

Pankanti, S., Bolle, R. M., & Jain, A. (2000). Biometrics: The future of identification. *Computer*, 33(2), 46–49.

Pato, J. N., Millett, L. I., Council, N. R., Committee, W. B., et al. (2010). Cultural, Social, and Legal Considerations. In *Biometric Recognition: Challenges and Opportunities*. National Academies Press (US).

Pereira, T. & Marcel, S. (2022) Fairness in biometrics: A figure of merit to assess biometric verification systems, *IEEE Transactions on Biometrics, Behavior, and Identity Science*, 4(1), 19-29.

Perez, L. M., Jones, M. J., Englert, D. R., & Sachau, D. (2010). Secondary Traumatic Stress and

- Burnout among Law Enforcement Investigators Exposed to Disturbing Media Images. *Journal of Police and Criminal Psychology*, 25(2), 113–124.
<https://doi.org/10.1007/s11896-010-9066-7>
- Peters, P. J. (2022). Technology-facilitated child abuse. In R. Geffner, J. W. White, L. K. Hamberger, A. Rosenbaum, V. Vaughan-Eden & V. I. Vieth (Eds), *Handbook of interpersonal violence and abuse across the lifespan* (pp. 953-973). Springer Nature Switzerland AG.
- Peterson, B. (2023, September 28). The Average Person Has 2,795 Photos in Their Phone. *DRGNews*. Retrieved March 8, 2024 from <https://drgnews.com/2023/09/28/the-average-person-has-2795-photos-in-their-phone/>
- Planells Garcés, J. F. (2022). Manual de policía científica: entre la teoría y la experiencia (1a edición). [Scientific police manual: between theory and experience (1st edition)]. Valencia, Espana: Tirant lo Blanch.
- Ravikanth, C. & Kumar, A. (2007). Biometric authentication using finger-back surface. *IEEE Conference on Computer Vision and Pattern Recognition*, Minneapolis, MN, USA, 2007, pp. 1-6, doi: 10.1109/CVPR.2007.383390.
- Ring, T. (2016). How the biometrics industry can help stop child abuse. *Biometric Technology Today*, 2016(11), 9-11.
- Ringenberg, T., Seigfried-Spellar, K. C., Rayz, J. M., & Rogers, M. K. (2022). A scoping review of child grooming strategies: Pre- and post-internet. *Child Abuse & Neglect*, 123, 1-12.
- Seigfried-Spellar, K. C. (2017). Assessing the Psychological Well-being and Coping

- Mechanisms of Law Enforcement Investigators vs. Digital Forensic Examiners of Child Pornography Investigations. *Journal of Police and Criminal Psychology*, 33(3), 215-226.
- Seigfried-Spellar, K. C. (2020). *Chat Analysis Triage Tool for Child Sex Offender Chats*. Presentation at the 2020 National Cyber Crime Conference (NCCC). Virtual Edition: July 13-17, 2020.
- Seigfried-Spellar, K. C. (2021). *Chat Analysis Triage Tool (CATT): A Digital Forensics Tool for the Language-Based and Biometric Analysis of High-Priority Child Sex Offenders*. Europol's Forensic Experts Forum (FEF 2021). Virtual: November 22-26, 2021.
- Simonyan, K. & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition. Retrieved from <https://arxiv.org/abs/1409.1556>
- United States Department of Justice. (2016). *The national strategy for child exploitation prevention and interdiction: A report to congress*. Retrieved from <https://www.justice.gov/media/857721/dl?inline>
- Usha, K. & Ezhilarasan, M. (2015). Finger knuckle biometrics—A review. *Computers & Electrical Engineering*, 45, 249–259.
- Vanderkolk, J. R. (2012). Examination methodology. In A. McRoberts (Ed), *The Fingerprint Sourcebook* (pp. 1-26). National Institute of Justice: Washington DC.
- Vyas, R., Rahmani, H., Boswell-Challand, R., Angelov, P., Black, S., & Williams, B. M., (2021). *Robust end-to-end hand identification via holistic multi-unit knuckle recognition*. Proceedings of the 2021 IEEE International Joint Conference on Biometrics (IJCB). *IEEE*, pp. 1–8.
- WeProtect Global Alliance. (2023). *Global threat assessment 2023: Assessing the scale and*

scope of child sexual exploitation and abuse online, to transform the response. Accessed April 20, 2024 from <https://www.weprotect.org/global-threat-assessment-23/#full-report>

Woolf, M. (2023, November 20). *18+ Mobile Photography Statistics for 2024*. PhotoAid. Retrieved March 1, 2024 from <https://photoaid.com/blog/mobile-photography-statistics/>