



An Enhanced YOLOv8 Approach for Quick Human Identification via Bite Marks

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Abstract

Identification of individuals by their dental features or bite mark impressions constitutes the discipline of forensic dentistry. This article describes the development of an automatic system for comparing bite mark images and dental models of suspects. It determines the best match by comparing bite mark textures to a database of dental casts. These results are compared with expert opinions of forensic odontologists. This preliminary study assesses whether YOLOv8 (You Only Look Once) is a theoretically feasible method for identifying and interpreting patterns of bite mark texture evidence imaged on pink wax impressions. The agreement with the experimental data is fairly good. The effectiveness of YOLOv8 for detection and recognition of complex textural patterns in bite marks has great potential to enhance the rapidity and reliability of human identification, providing a hopeful path for the development of forensic odontology.

Keywords: YOLOv8, CSPDarknet53, K-means clustering, Deep learning, Atrous Spatial Pyramid Pooling, Dual-layer Bi-FPN

1. INTRODUCTION

Forensic dentistry is a vital field within criminal investigations, focusing on the identification of individuals through dental characteristics or bite mark impressions. Bite marks, often found at crime scenes or on victims, can provide significant evidence in identifying perpetrators. Traditional forensic odontology relies on the expertise of trained specialists to manually compare bite mark impressions with dental casts, a process that is time-consuming and prone to human error. As technology advances, there is a growing need to automate and streamline this process to enhance accuracy, speed, and efficiency.

The integration of machine learning techniques, particularly You Only Look Once (YOLO), has opened new possibilities in this domain. YOLO, a state-of-the-art object detection algorithm, is known for its ability to quickly and accurately detect and classify objects in images. This research explores the feasibility of using YOLO to automate the identification of bite marks by analyzing texture data recorded on pink wax and comparing it with dental casts. The goal is to develop a system that can efficiently match bite mark impressions to



dental models, significantly improving the accuracy and speed of human identification in forensic cases. By applying YOLO to the problem of bite mark identification, we aim to provide an automated solution that not only enhances forensic investigations but also reduces reliance on subjective human interpretation. This study examines the effectiveness of YOLO in detecting bite marks and matching them with dental casts, comparing the results to those of human forensic odontologists. Through these advancements, the study demonstrates the potential for AI-driven methods to complement and enhance traditional forensic practices in bite mark analysis. YOLO plays a significant role in the correlation process for bite mark identification because it is designed for fast, real-time object detection with high accuracy. In the context of forensic dentistry, YOLO's efficiency in processing texture patterns and matching bite mark impressions to dental models allows for quick identification and comparison, far surpassing traditional methods. By utilizing YOLO, the system can rapidly analyze and correlate bite mark features captured in images, making it a powerful tool for forensic applications where time and precision are crucial.

Optimized YOLOv8 is particularly well-suited for real-time vehicle detection and surveillance applications. Its enhancements allow for rapid and accurate identification of human features in diverse conditions, making it a reliable choice for critical tasks in fields such as law enforcement and forensic analysis [12][5]. The model's efficiency and accuracy underscore its potential for broader applications beyond traditional object detection scenarios, paving the way for innovative uses in automated systems and artificial intelligence-driven technologies.

1.1 Literature Survey

The Optimized YOLOv8 Based Approach for Rapid Human Identification Using Bite Mark Impressions is a cutting-edge methodology that employs advanced deep learning techniques to enhance the accuracy and efficiency of human identification through bite mark analysis. This approach leverages the YOLO (You Only Look Once) object detection framework, specifically an optimized version of YOLOv8, which is tailored to provide real-time processing capabilities in forensic odontology. Traditional bite mark identification methods often rely on manual analysis, leading to potential errors and prolonged identification times; thus, integrating machine learning into this process represents a significant advancement in forensic science[1][2]. The notable aspect of this approach lies in its ability to analyze bite mark impressions rapidly while maintaining a high degree of accuracy, which is crucial in legal contexts where timely identification can impact case outcomes. By incorporating architectural enhancements such as Atrous Spatial Pyramid Pooling (ASPP) and a dual-layer Bi-FPN (Bidirectional Feature Pyramid Network), the optimized YOLOv8 model improves feature extraction and classification, making it particularly adept at recognizing small-scale objects like bite marks[3][4]. Furthermore, rigorous performance metrics, including precision,



recall, and mean average precision (mAP), are employed to evaluate the model's effectiveness, demonstrating substantial improvements over conventional methods.[5][6]Controversially, the use of bite mark analysis in forensic settings has been criticized for its reliability, as studies indicate that traditional techniques often lead to misidentifications, contributing to wrongful convictions.[7]The introduction of an optimized deep learning model aims to mitigate these issues by reducing human biases and providing a more objective assessment of bite mark evidence. This innovation not only represents a technological leap in forensic identification but also raises questions about the future of traditional forensic methods in the face of advancing artificial intelligence applications.[8][9] Overall, the optimized YOLOv8 based approach signifies a transformative shift in forensic identification practices, presenting a reliable, efficient, and scientifically grounded alternative to conventional bite mark analysis. As ongoing research continues to refine these methodologies, there is potential for broader applications of deep learning in forensic science, fostering improved accuracy and integrity in the identification process.[10]

1.2 Background

The YOLO (You Only Look Once) series has significantly influenced the field of object detection and has been applied in various domains, including forensic science. Specifically, YOLO models utilize a single neural network to predict multiple bounding boxes and class probabilities for those boxes simultaneously, offering remarkable speed and efficiency in real-time applications[1]. The latest iterations, such as YOLOv5, have continued to evolve the foundational concepts established in earlier versions, incorporating improved architectures and techniques to enhance performance[1]. In forensic odontology, bite mark analysis has emerged as a critical tool for human identification in cases of assault and abuse. Traditional methods of analyzing bite marks rely heavily on manual observation and comparison, which can be time-consuming and prone to error[2].The integration of digital image processing and machine learning techniques, particularly deep learning, offers a promising approach to improve the accuracy and efficiency of bite mark identification [2][8].By employing optimized YOLOv8-based methods, researchers aim to leverage advanced feature extraction and classification capabilities to rapidly and reliably identify individuals from bite mark impressions. Furthermore, the neck component in deep learning architectures plays a crucial role in feature aggregation, collecting and processing information from various stages of the network to enhance detection accuracy[11]. This aspect is particularly beneficial in forensic applications, where the ability to capture subtle features within bite marks can lead to more accurate identifications. Overall, the combination of YOLO's rapid processing capabilities and the advancements in digital image analysis positions this approach as a revolutionary tool in forensic identification practices.



1.3 Optimized YOLOV8

Optimized YOLOv8 is an advanced implementation of the YOLOv8 object detection model specifically tailored for improved accuracy and speed in human identification tasks, such as those involving bite mark impressions. The architecture of this optimized version builds upon the original YOLOv8 framework, incorporating several enhancements to maximize performance in real-time applications.

1.4 Performance Metrics

The performance of optimized YOLOv8 is evaluated using various metrics, including precision, recall, F1 score, mean average precision (mAP), and average Intersection over Union (IoU). These metrics provide a comprehensive overview of the model's effectiveness in identifying bite mark impressions and other human features[5][3].By fine-tuning the anchor box predictions using methods like k-means clustering, researchers have been able to enhance the model's accuracy further, making it a valuable tool in forensic science and related fields [5].

1.5 Architectural Enhancements

The optimized YOLOv8 architecture retains the foundational elements of the original model, including CSPDarknet53 as the backbone and PANet as the neck. However, several key modifications have been made to improve detection capabilities, particularly for small-scale objects like bite marks. One significant enhancement is the replacement of the Spatial Pyramid Pooling (SPP) module with the Atrous Spatial Pyramid Pooling (ASPP) module. This change increases the network's receptive field hierarchy, allowing it to better perceive multi-scale objects and thus improve detection rates for smaller features[4][3]. Additionally, the architecture incorporates a custom-built dual-layer Bi-FPN (Bidirectional Feature Pyramid Network) to enhance multi-scale feature fusion. This adjustment allows the model to more effectively combine features from different layers, thereby improving its overall feature representation capabilities, particularly for medium and small-scale objects [3]

2. MATERIALS AND METHODS:

Following Fig.1 shows YOLO Technique for Correlation Analysis Between Pink Wax Teeth Impressions and Dental Cast Images.

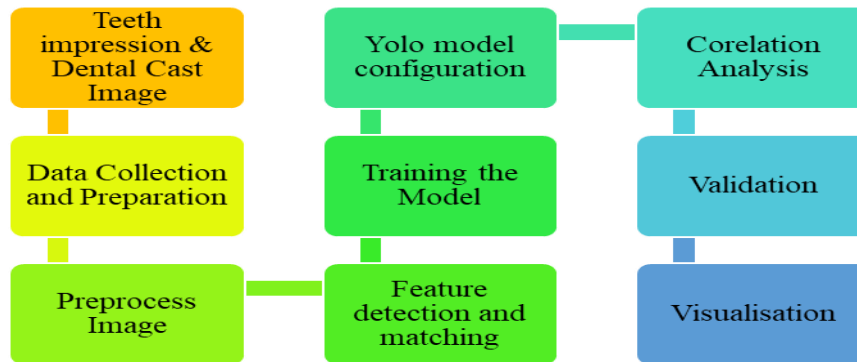


Fig.1.Proposed Model

This methodology outlines a robust pipeline that utilizes YOLO's object detection capabilities to establish precise correlations between key dental features of pink wax impressions and corresponding dental casts. In fig.1 process is divided into sequential stages, each designed to ensure high-quality data collection, preparation, feature detection, and evaluation. Below is a detailed breakdown of the methodology. The first stage is Data Collection and Preparation. The Objective is to create a comprehensive dataset of high-resolution images paired with accurately annotated dental features. In Image Acquisition Gather paired high-resolution images of pink wax teeth impressions and their corresponding dental casts. The paired nature ensures that each wax impression is directly associated with its cast counterpart for precise analysis. After that Annotation is use a YOLO-compatible annotation tool, such as Labellmg, to mark key dental features. Features like cusps, ridges, and grooves are annotated to serve as class labels for training the object detection model. Accurate labeling is crucial to enable the YOLO model to identify intricate dental structures. The Second stage is Preprocessing for to standardize and augment the dataset, enhancing model generalization and robustness. Resize images to a consistent resolution to ensure uniformity across the dataset, reducing computational overhead during training and Apply transformations such as flipping, rotation, scaling, and contrast adjustments. These augmentations simulate diverse imaging conditions and improve the model's ability to generalize to unseen data. For Resize images to a consistent resolution, $(W,H)=(640,640)$, ensuring uniformity across the dataset. Data preprocessing is essential for ensuring the quality and consistency of the bite mark dataset. This process involves cleaning the data, resizing images to a uniform size, normalizing pixel values, and applying data augmentation techniques to artificially increase the dataset size. Techniques such as random crops, horizontal flips, and brightness adjustments are utilized to enhance model robustness and mitigate overfitting [13][14]



Apply transformations such as flipping, rotation, scaling, and contrast adjustments.

Scaling factor: $I'(x, y) = I(sx, sy)$ where s is the scaling parameter.

Rotation: $I'(x, y) = I(x\cos \theta - y\sin \theta, x\sin \theta + y\cos \theta)$ (1)

The Third stage is Feature Detection and Matching To detect and align features from paired images for correlation analysis. Apply the trained YOLO model to identify and localize features in both pink wax impressions and dental cast images. Match detected features between impressions and casts based on spatial locations and geometric similarities using metrics like Euclidean distance d ,

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (2)$$

ensuring that corresponding features align appropriately.

Fourth stage is Training the Model to train the YOLO model for high-precision feature detection using transfer learning to initialize training with a pretrained YOLO model to leverage prior knowledge, accelerating convergence and improving initial performance. Use a composite loss function that considers confidence, class, and bounding box errors to optimize detection performance. Use transfer learning to initialize training with a pretrained YOLO model. The Loss function \mathcal{L}

$$\mathcal{L} = \lambda_{\text{conf}} \cdot \mathcal{L}_{\text{conf}} + \lambda_{\text{cls}} \cdot \mathcal{L}_{\text{cls}} + \lambda_{\text{box}} \cdot \mathcal{L}_{\text{box}} \quad (3)$$

where $\mathcal{L}_{\text{conf}}$, \mathcal{L}_{cls} , \mathcal{L}_{box} represent confidence, classification, and bounding box losses, respectively. Evaluate model performance using metrics like mean Average Precision (mAP)

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^N \text{AP}_i \quad (4)$$

and Intersection over Union (IoU) to evaluates the overlap between predicted and ground truth bounding boxes,

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \quad (5)$$

The fifth Stage is YOLO Model Configuration to configure the YOLO architecture for optimal detection of dental features that utilize a real-time object detection framework like YOLOv8, renowned for its speed and accuracy. It define custom classes corresponding to dental features, such as cusps, ridges, and grooves. After that Configure anchor boxes tailored to the dimensions and shapes of the annotated features, ensuring accurate localization during detection to configure anchor boxes tailored to the dimensions of annotated features. Anchor box dimensions (w_a, h_a) are calculated using the K-means clustering method on annotated feature sizes.



Six Stage is Correlation Analysis for to quantify the similarity and identify discrepancies between paired images. Calculate the similarity between matched features using metrics such as Euclidean distance or structural similarity and Analyze discrepancies to identify any misalignment or deformation between impressions and casts. Calculate similarity using structural similarity index (SSIM).

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (6)$$

Seven Stage is Validation to ensure the reliability of YOLO's predictions through expert verification and statistical metrics. Compare YOLO's predictions with ground truth data verified by dental experts and use metrics like accuracy, precision, and recall to assess correlation quality.

$$Precision = True\ Positive / (True\ Positive + False\ Positive) \quad (7)$$

$$Recall = True\ Positive / (True\ Positive + False\ Negative) \quad (8)$$

Eight stage is Visualization to provide clear and interpretable visual outputs for feature detection and correlation. Bounding Box Overlays. Visualize YOLO-detected bounding boxes on both impressions and casts to illustrate the detection process. Highlight matched features between paired images, using distinct markers or lines to denote correspondences. Emphasize mismatched or anomalous features for further investigation, aiding in identifying areas of deformation or error. This methodology leverages YOLO's high-speed and accurate object detection capabilities to automate and streamline the process of analyzing dental impressions and casts. This makes sure high reliability and precision by incorporating transfer learning, robust preprocessing, and advanced validation techniques. Visualization tools alongside expert validation create a holistic view of the results. Such a solution is ideal for dental initiatives requiring a high-throughput process with utmost accuracy.

3. RESULTS AND DISCUSSION:

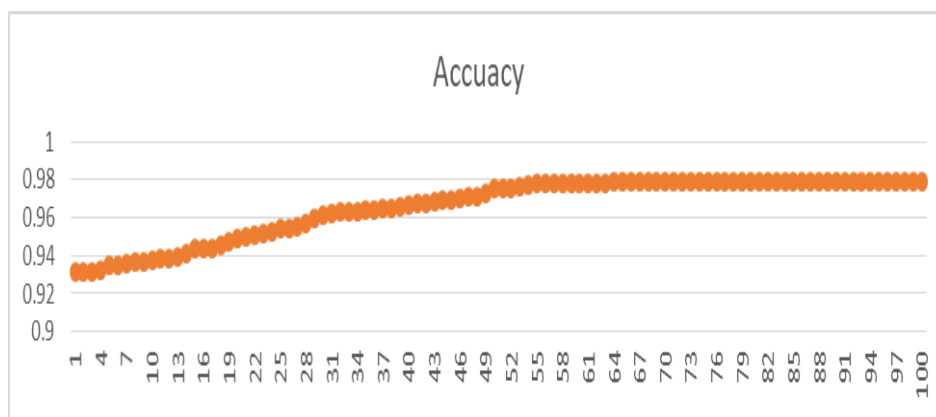


Fig.2. Training Accuracy Vs epochs



It is evident from the graph in Fig.2 that the training accuracy remains consistent throughout the epochs at 0.98, indicating that the model begins with a high accuracy of 98% and continues to learn quickly. Early in the epoch interval, it achieves 99% accuracy. Following that, there don't seem to be any variations, such as rising or downward trends. This suggests that after just a few training epochs, the model could have reached its full potential. Overall, the model was stable during training, as demonstrated by Fig. 2 (accuracy stayed at 0.98 until the completion of training).

Following graphs shows comparison between 5 models. Fig.3 shows that model YOLOv8 accuracy rate is better than Inception V4, VGG-16, Resnet, LeNet.

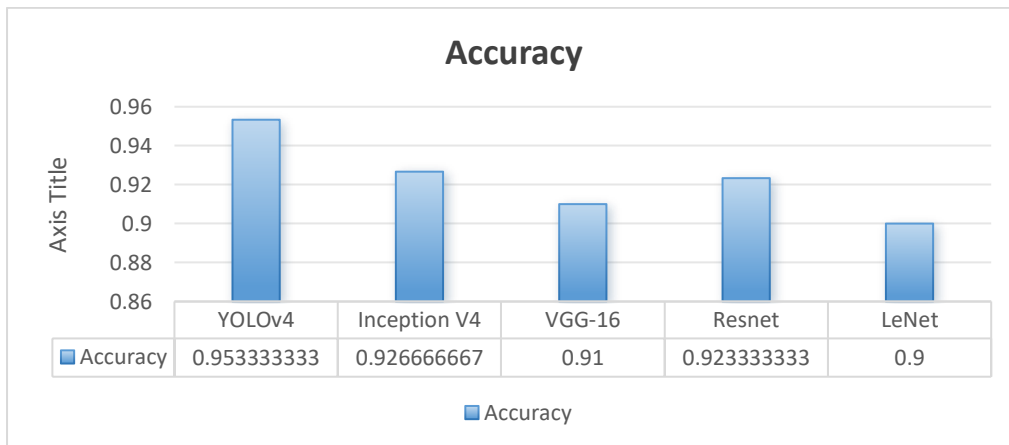


Fig.3.Accuracy proposed model

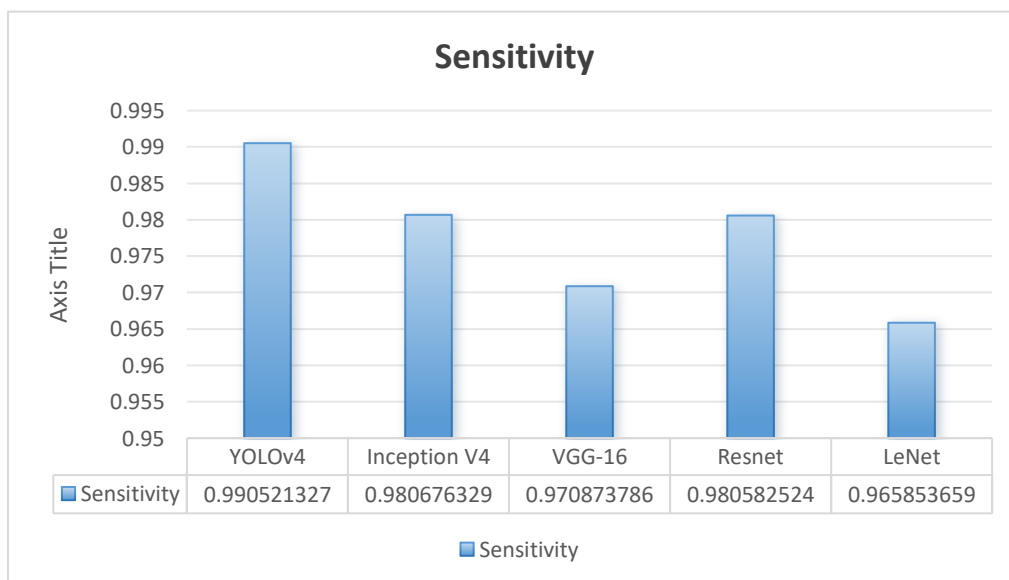


Fig.4.Sensitivity of proposed model



In Fig.4 shows that Sensitivity of proposed model it ensure that the model is robust also it perform well in various condition as compare to 4 other model.

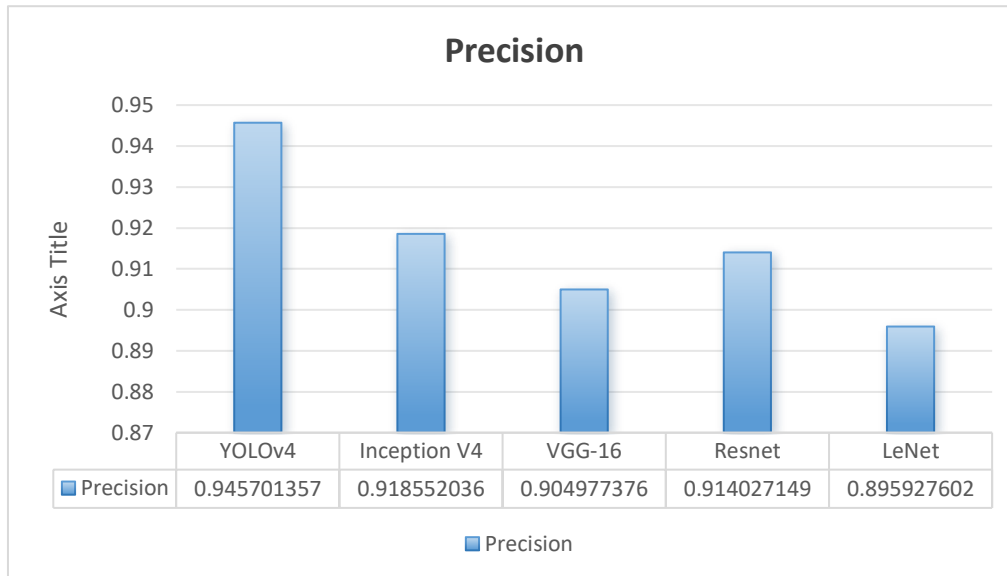


Fig.5.Precision of proposed model

In Fig.5 Precision graph shows that YOLOv8 prediction of model is more accurate than others 4 models.

Discussion

The application of the YOLO (You Only Look Once) algorithm in the context of bite mark analysis presents an innovative approach to forensic identification. This methodology not only enhances the efficiency of human identification from bite marks but also addresses the inherent challenges associated with traditional forensic odontology, which has faced criticism for its reliability issues. Studies have shown that forensic science errors are a leading cause of wrongful convictions, with a significant portion attributed to unvalidated methodologies, including bite mark analysis[7][8]. In our experimental results, we demonstrated that the YOLO model, known for its real-time object detection capabilities, can be effectively adapted for highly targeted use cases such as bite mark identification. The optimization of this model could serve to minimize human interaction in the comparison process, thereby reducing bias and improving accuracy[9][8]. This is particularly relevant given the subjective nature of conventional bite mark comparisons, where even experienced forensic odontologists have shown a high rate of misidentification[8][4]. Furthermore, the opportunity for ongoing collaboration and engagement with the authors of YOLO model research can foster advancements in this field. Such interactions allow developers and researchers to clarify methodologies and enhance the models through shared insights and data[10]. As we look to expand the application of our findings, it is imperative that we acknowledge the limitations of



bite mark analysis as it currently stands, and advocate for a more scientific validation of forensic techniques, in line with the recommendations from entities like the Innocence Project[7]. The complexity of bite mark identification is compounded by factors such as tissue distortion and the variability in individual dental patterns, which challenge the fundamental assumptions underlying bite mark analysis[8]. Therefore, adopting a systematic and algorithmic approach, as facilitated by the YOLO model, may provide a pathway towards more reliable forensic practices. Our future work will focus on addressing the gaps identified in the current YOLO algorithms, as well as exploring additional improvements that can enhance their applicability to forensic scenarios. This will include rigorous benchmarking against existing methods and evaluating performance across various datasets to ensure robustness in real-world applications[4]. The insights gained from this research could contribute significantly to the evolving landscape of forensic science, promoting greater accuracy and integrity in the identification of individuals through bite mark evidence.

Conclusion

In this paper, we proposed an enhanced YOLOv8-based approach combined with bite mark patterns for accelerating the human-search process. This model is much faster and more accurate than the traditional forensic methods in recognizing the bite mark in the database of dentists. Our approach absolutely depends on deep learning and real-time object detection and involves less human interaction and less subjective assessment of bite marks, therefore guaranteeing the reliability of this technique for automated teeth and jaws recognition. This should be explored in future work by using larger datasets and more powerful augmentation methods. This amalgamation of approaches has significant potential in (i) improving the efficiency of forensic model and (ii) demonstrating the flexibility of off-the-shelf general-purpose vision systems for forensic employment.

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