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Image Processing-Based Application for Determining Wound Types in Forensic Medical Cases

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A B S T R A C T

Wounds result from physical violence that damages the continuity of body tissues and are frequently observed in forensic medicine and medicolegal science. In forensic medicine and medicolegal science, wounds play a significant role in creating a medicolegal examination and report (VeR) for deceased individuals and living victims. However, research findings indicate that the quality of clinical forensic descriptive results in VeR needs to improve in several hospitals in Indonesia. Meanwhile, high-quality VeR results are crucial in determining penalties for perpetrators in court, and poor VeR results can hinder the legal process. The application of information technology in medicine has yielded numerous tools that can assist experts in carrying out their duties. Likewise, clinical forensics, a generally conservative forensic pathology practice, can be enhanced through image-processing techniques and machine learning. Digital technology support for forensic cases has been available previously, such as in forensic photography; however, its application still needs improvement, and further development is required. This study applied a Yolo V4-based machine learning and image processing algorithm to classify and detect types of wounds. This algorithm was chosen for its high speed and accuracy in classification and detection tasks. The research results showed that the learning model's performance, measured in accuracy, precision, recall, and average F1 score, reached 92%. Usability testing showed that the system performed well and could be helpful with minor improvements.

INTRODUCTION

In forensic medicine and medicolegal science, wounds play a significant role in the creation of a medicolegal report (VeR) for both deceased individuals and living victims. VeR is a document requested by investigative authorities (the police) from medical professionals concerning wounds to the human body. This document serves as evidence in the judicial process, which not only adheres to medical record writing standards but also fulfills the requirements of the legal system [1]. Based on a study on the clinical forensic description quality of VeRs in Yogyakarta from 2011 to 2016, all hospitals fell into a moderate category (ranging from 50% to 75%) due to the absence of photographic documentation of wounds [2]. Research on the quality of VeR outcomes in Jakarta and Pekanbaru revealed that the quality of the conclusion section was 65.94% (moderate quality) in Jakarta and 37.5% (poor quality) in Pekanbaru. Although 68.9% of doctors could identify the type of wound and violence, 62% of doctors could not correctly assess the qualification of wounds.

Furthermore, in a study in Pekanbaru, none of the doctors examining VeR included the wound qualifications under Articles 351, 352, and 90 of the Criminal Code (KUHP) [3]. High-quality VeR outcomes are crucial in determining the punishment for perpetrators in court, while poor VeR outcomes can hinder the legal process [4]. Forensic examination of wounds includes determining the type of wound, the kind of violence, and the extent of the wound. In other words, it must adhere to the formulations specified in the Criminal Code [5]. Clinical decision variations can occur in determining the degree of wound from assault, which can detrimentally impact the judicial process. Understanding the medicolegal aspects and determining the degree of the wound is necessary to improve the quality of wound VeRs that meet the standards. With the rapid advancement of technology, computer-aided diagnostic systems are gaining acceptance. The application of information technology in medicine has created many tools that can support the work of professionals [6]. Likewise, in the traditionally conservative field of clinical forensics, image-processing techniques can be reliably used as a decision-support system [7].

During examination, wounds are identified based on visual inspection, where a physician identifies the wounds using geometric measurements and assesses the involved skin tissues [8]. The ability to embed imaging technology in portable devices such as smartphones and tablets could significantly enhance the

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speed of wound interpretation. By integrating multiple imaging modalities and machine learning, the system could possess powerful wound identification capabilities, thus expediting the interpretation of wounds [9]. Several studies have related to image processing applications in clinical forensics, such as using dental radiograph images for postmortem and antemortem forensic comparisons based on image processing [5][6]. One of the advantages of image processing techniques is their ability to extract representative features and descriptions. Each object in the image can typically be classified based on its unique characteristics, such as natural features (color and texture) or artificial features (amplitude histograms and frequency spectrum) [10]. The goal of feature extraction is to describe objects and discover unique attributes that can differentiate one image from another; the obtained features are then used for classification [10].

In general, feature extraction methods in wound-related cases are broadly categorized into three main approaches: rule-based feature extraction, machine learning-based feature extraction, and deep learning-based feature extraction [11]–[14]. Previous research in image processing for forensic cases has identified several critical areas for further improvement. The first is the sufficient use of large datasets to develop high-performing systems [15]–[17]. Second, appropriate segmentation methods to detect wound edges in detail are selected as some algorithms struggle with detecting small or irregularly shaped wounds [14], [18]. Third, implementing preprocessing stages, such as contrast enhancement, sharpening, and smoothing, is necessary to enhance image quality[19]. Lighting, contrast, and image quality significantly affect the system's detection outcomes. Fourth, supervised learning algorithms remain the most commonly used for machine learning purposes. Fifth, an algorithm that achieves a high accuracy rate (>80%) is currently needed, and the sixth and final point is that most wound detection cases are oriented toward medical treatment rather than forensic purposes. This research aimed to develop a system capable of analyzing wound types to create high-quality clinical forensic descriptions (VeR). The technology developed to address this issue was an image processing and machine learning-based system that determined the type and size of the wound.

METHOD

Data

The data used in this research consisted of forensic wound images from Bhayangkara Hospital. A research permit to conduct this study was obtained from the hospital (number B/148/III/DIK.2.6/2023/Rumkitbhy). The research data comprised 494 wound images, categorized into four classes: shear abrasion, compression abrasions, contusions, and lacerations. Figure 1 illustrates each class of wounds. During the training and testing processes of the classification algorithm, the wound data were divided into two subsets: training data and testing data. The training data constituted 90% of the total data, while the rest was testing data. Details of the training and testing dataset are given in Table 1.

Table 1. Details of the training and testing dataset

No	Wound Types	Training data	Testing data
1	shear abrasion	110	25
2	compression abrasion	104	26
3	contusions	98	24
4	lacerations	93	23
	Total	**396**	**98**

Wound Definition

Abrasion Wound

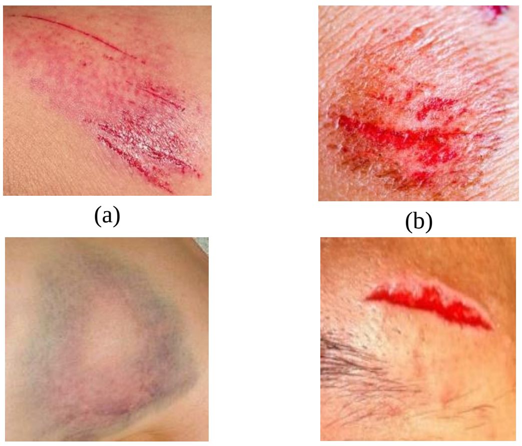
An abrasion wound occurs when applied force moment causes contact between the body's surface and an object's surface, resulting in friction that causes the superficial layer of the skin to rub. If the direction of the force moment is perpendicular to the skin's surface, it results in a compression abrasion wound. When the force moment arrives at an angle between 0 to 90 degrees, it leads to shear abrasion wounds.

Laceration Wound

A laceration wound occurs when the kinetic force generated during the interaction between the body and an impact exceeds the tissue's elastic capacity and mechanical strength. This type of wound is characterized by irregular wound edges, the presence of tissue bridges, and the edges displaying an irregular pattern when both sides of the wound are approximated.

Contusion (Bruise)

A contusion, commonly known as a bruise, is an injury caused by blunt force to the body, resulting in the blood vessels in the affected area bursting and leaking blood into the surrounding tissues. At the same time, the skin surface remains intact.



(a) (b) (c) (d)

Figure 1. (a) shear abrasion, (b) compression abrasions, (c) contusions, (d) lacerations

Learning Algorithm

In this research, the Yolo V4 algorithm was employed. Yolo is categorized as a one-stage detector algorithm with advantages for detection speed. This study aimed to develop a wound-detection

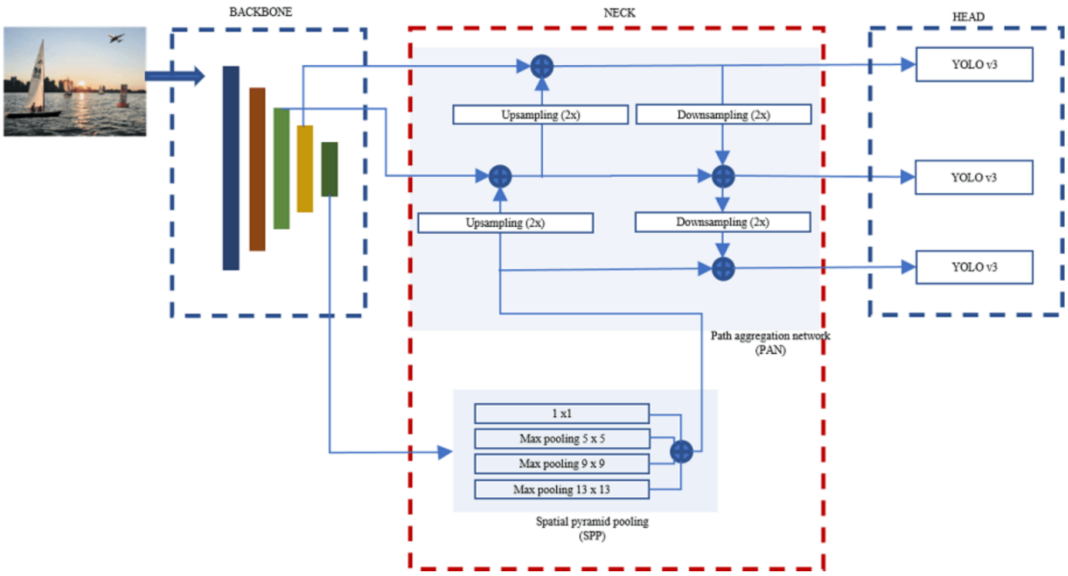


Figure 2. Yolo's main components [20]

and classification system that could be used in real-time scenarios where detection speed is a crucial factor while maintaining the accuracy of detection results. Yolo consists of three main components: the backbone, neck, and head, as illustrated in Figure 2.

Training Model Steps

In this phase, the model training process was conducted, comprising the following stages: (1) data augmentation, (2) object labeling, (3) data extraction, (4) training, and (5) testing.

Augmentation

In the initial preprocessing stage, image augmentation was performed through rotation or cropping techniques to balance the dataset by ensuring an equal number of samples per class.

Object Labeling

Labeling and bounding boxes were applied to objects in this stage to provide distinctive attributes for each object.

Data Extraction

This stage ran the process of recording data ***for training and testing data and extracted all images with extensions .jpg and .txt labeled*** into .rar extensions. The .rar files contained all information about the images and the location of the object bounding boxes.

Training Model Process

Object detection models could be developed by custom object detector training. The wound data training process used Google Collaboratory**,** supported by the Roboflow platform, and the PyTorch framework as the training data repository.

Testing Model Process

Model testing involved using a separate set of testing data prepared independently from the training data. Several parameters were measured, including accuracy, precision, recall, and F1 score.

Evaluation Method

The model evaluation process used the confusion matrix method to obtain true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values. These values were then used to calculate accuracy, precision, recall, and F1 score sequentially in equations (1), (2), (3), and (4). The confusion matrix may provide a more comprehensive evaluation approach that gives engineers deeper insights into their model's performance. The confusion matrix method used a table to store information about the comparison between the system's classifications and the actual classifications of the data, as illustrated in Figure 3.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \times 100\% \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (3)$$

$$F1\ Score = \frac{2\times(Recall\times Precision)}{Recall+Precision} \times 100\% \quad (4)$$

		Actual Class	
		1	**0**
Predicted Class	**1**	True Positive (TP)	False Positive (FP)
	0	False Negative (FN)	True Negative (TN)

Figure 3. Confusion Matrix

Application Development

Qt-Designer was used to design the user interface (UI) and execute the application using Visual Studio. Once the UI design work was completed, the files were saved in the .ui format and converted to .py format to make them readable in Visual Studio. Several libraries ran the application, including OpenCV, Python PyQt5, and Imutils.

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System Usability Scale

The system usability scale (SUS) is a testing method to measure user satisfaction. This is a 10-question questionnaire designed for users/respondents. Scoring rules are applied individually to each respondent. Then, the average SUS score for all respondents is calculated by summing all the scores and dividing them by the number of respondents, as shown in equation (5).

$$\bar{x} = \frac{\sum x}{n} \quad (5)$$

Where:
$\bar{x}$: average SUS score
$\sum x$: SUS total score
n : total number of respondents

RESULTS AND DISCUSSION

In this research, parameter tuning was conducted for Yolo V4 to generate an accurate prediction model through a trial-and-error process. The experimentation yielded an optimal parameter combination, as listed in Table 2.

Table 2. Training Parameter

Configuration Types	Value
Batch	64
Subdivisions	16
Width	416
Height	416
Max Batches	8000
Steps	6400,7200
Classes	4
Filters	27

The model was repeatedly trained to achieve a low average loss. In machine learning, average loss is often associated with loss of function, which assesses how well a model predicts outcomes. This research demonstrated a shallow training loss rate, precisely 0.1996 at iteration 7910, as illustrated in Figure 4.

To determine the appropriate data split ratio between training and testing datasets during training and evaluation, a data comparison was conducted between two data division scenarios 90:10 and 20:80, with the assessment of the learning rate based on the average Intersection over Union (IoU) and loss values, as shown in Table 3. IoU is a metric that assesses the system's accuracy in detecting objects in the trained dataset. IoU compares ground-truth objects in the images with the predicted bounding boxes generated by the model. High IoU values and low loss values are desired to achieve an optimal system. In this study, the parameter configuration was carried out using a dataset split with a learning rate value 0.001.

Table 3. Learning rate measurement of data splitting

	90:10	**80:20**
IoU	79.14%	74.40%
Loss	0.0553	0.0594

Based on the results in Table 3, a data split of 90% and 10% was determined for this study.

The matrix test results are shown in Table 4 after the model was tested.

Table 4. Confusion matrix of test results

	Shear abrasion	**Compression abrasion**	**Contusions**	**Lacerations**	**Total**
Shear abrasion	22	2		2	26
Compression abrasion	1	24			25
Contusions			24		24
Lacerations		2		21	23
Total	23	28	24	23	**98**

Table 4 shows that the model's classification performance is relatively strong as it yields only a limited number of false negatives. The calculated accuracy, precision, recall, and F1 scores are provided in Tables 5, 6, 7, and 8, respectively.

Table 5. Results of accuracy measurement

Performance Indicator	Shear abrasion	Compression abrasion	Contusions	Lacerations
TP	22	24	24	21
FP	4	1	0	2
Total	26	25	24	23
Accuracy	**0.84**	0.96	**1**	0.91

Accuracy is an evaluation metric that measures the extent to which a classification model accurately predicts overall classes. While accuracy provides an overall picture of the model's performance, there may not be other suitable evaluation metrics when dealing with imbalanced datasets. In this research, acquiring sufficient data for each class was challenging, especially for the type of lacerations wounds. Therefore, we performed data augmentation during the preprocessing stage to balance the data among classes. In our test data, we also applied stratified random sampling to ensure that the test data could be randomly selected while representing an equal number of samples for each class. This indicates that using accuracy as an evaluation metric is an appropriate performance measure to assess how well the model performs. Table 5 shows that the model performs well; however, the model's ability to classify shear abrasions remains lower than other wound types. Since shear abrasions are nearly identical to compression abrasions, even a forensic expert must meticulously examine them to differentiate between the two. One way to enhance the model's ability to distinguish between these two types of wounds is to increase the amount of training data.

Table 6. Results of Precision Measurement

Performance Indicator	Shear abrasion	Compression abrasion	Contusions	Lacerations
TP	22	24	24	21
FP	4	1	0	2
Precision	**0.84**	0.96	**1**	0.91

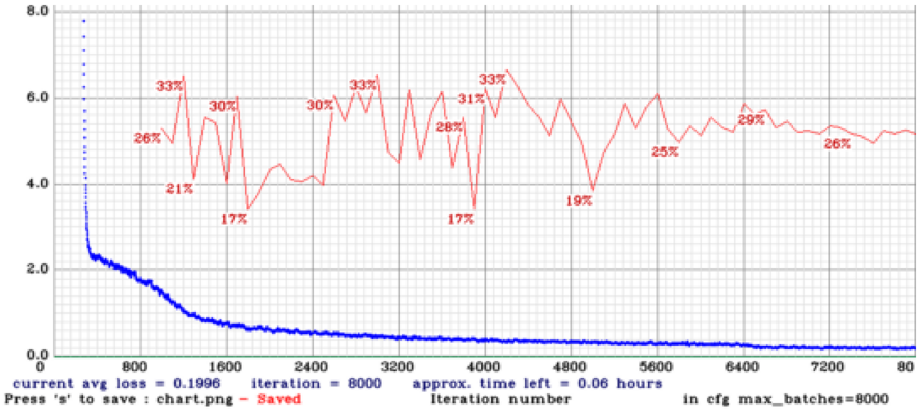

Figure 4. Average loss

The precision performance parameter was used to gauge the extent to which the model's optimistic predictions correctly corresponded to actual positive instances. Precision is valuable when the objective is to minimize the number of false positives. Table 6 shows that the model generates insufficient false positives, accounting for only 0.07% of the total testing dataset, indicating minimal false positives.

Table 7. Results of Recall Measurement

Performance Indicator	Shear abrasion	Compression abrasion	Contusions	Lacerations
TP	22	24	24	21
FN	1	4	0	2
Recall	**0.96**	0.84	**1**	0.91

The precision performance parameter was used to gauge the extent to which the model's optimistic predictions correctly corresponded to actual positive instances. Precision is valuable when the objective is to minimize the number of false positives. Table 7 shows that the model generates insufficient false positives, accounting for only 0.07% of the total testing dataset, indicating minimal false positives.

Table 8. Results of F1 score Measurement

Performance Indicator	Shear abrasion	Compression abrasion	Contusions	Lacerations
Precision	0.84	0.96	1	0.91
Recall	0.96	0.84	1	0.91
F1 Score	0. 89	0.89	1	0.91

An F1 score is a composite metric that measures the balance between precision and recall. It is useful when we need to consider both false positives and false negatives. The F1 score is the harmonic mean of precision and recall. It provides a better assessment than accuracy in situations where the dataset is unbalanced or the difference between false positives and false negatives is significant. The results in Table 8 demonstrate a good F1 score achievement as it approaches a value of 1.

Table 9 summarizes the model's performance, with an average achievement of approximately 92%. Table 10, on the other hand, provides an overview of the findings of previous research.

Table 9. Results of model performance

Wound Types	Accuracy	Precision	Recall	F1 Score
Shear abrasion	84%	84%	96%	89%
Compression abrasion	96%	96%	84%	89%
Contusions	100%	100%	100%	100%
Lacerations	91%	91%	91%	91%
Average	**92.75%**	**92.75%**	**92.75%**	**92.80%**

The data presented in Table 10 was not intended for direct comparison due to differences in the research but to demonstrate that the proposed study maintained competitive performance within the same field. The contribution of this research lies in the development of a real-time detection method implemented through an application-based approach. Notably, our research introduced a novelty in both data and problem domains. The primary data source used in our study was derived from records of forensic activities, and the problem addressed was related to wound classification for forensic purposes. Most previous studies focused on healing and analyzing diabetic wounds.

Table 10. Comparison with previous research

Author	Method	Data	Performance Evaluation
Manu et al. [12]	e Fully Convolutional Networks (FCNs)	Diabetic Foot Ulcer	Dice: 89% Specificity: 99% Sensitivity: 90% MCC: 89%
Changhan et al. [21]	Deep Convolutional Neural Networks	NYU Database (Wound surface area)	Accuracy: 95,6% Recall: 30.8% Precision: 40% F1-score: 0.348
Xiaohui Liu et al. [13]	Deep Convolutional Networks	no public dataset with pixel-level annotation	Accuracy: 98% mIoU: 84.6% DSC: 91.66%
Fangzhao Li et al. [14]	Deep Neural Networks	images from the Internet	mIoU: 85.32% MaxIoU: 85.8% Precision: 94.94%
Current research	Yolo V4	Private Data	Accuracy: 92.75% Precision: 92.75% Recall: 92.75% F1 Score: 92.80%

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After that, the system was implemented into an application. The application had three pages: a home page, which contained brief information about the application; a page for data input; and a page for results of detection, as shown in Figures 5, 6, and 7. Figure 5 shows the initial page of the application, providing a brief overview of the application's content. The main page had a "start detection" button, which, when clicked, redirected the user to the second page. Figure 6 illustrates the second page, where various menu options were available for inputting different data types, such as images, videos, and real-time videos.

Figure 7 displays the detection results. This page also featured a button for saving the images of the detection result, which medical professionals could use to document the outcomes of forensic examination. While using the application, we conducted observations based on the observed performance outcomes and identified several factors that could potentially contribute to detection errors, including:

Table 11 presents the differences in detection results between detailed and non-detailed labeling processes. The labeling phase played a crucial role in the model learning process. Given that the acquired wound images often varied in size and may contain multiple wound blocks that appeared as a single wound entity, it was essential to carry out meticulous and detailed labeling processes to maximize the model's performance in prediction.

Table 12 illustrates differences in detection outcomes based on the wound-to-camera distance. The camera's distance to the wound had a significant impact on the detection capability because the closer the camera was to the object or the larger the size of the detected object, the easier the detection process would be. Conversely, the farther the camera was from the object or the smaller the size of the detected object, the more challenging the detection process became.

The SUS questionnaire was used to test the system's usability. The questionnaire was completed by three respondents, comprising a forensic specialist doctor, medical specialization students (in the field of forensics), and undergraduate medical students. Table 13 presents the scores of the SUS questionnaire completed by these respondents.

Table 13. Results of SUS questionnaire

Respondent ID	R1	R2	R3
Question 1	5	4	4
Question 2	2	2	2
Question 3	4	4	4
Question 4	2	2	2
Question 5	3	4	5
Question 6	3	3	2
Question 7	4	4	4
Question 8	2	2	2
Question 9	5	5	4
Question 10	2	4	2

The total scores of respondents 1, 2, and 3, when multiplied by the constant 2.50, were 75, 67.50, and 77.50, respectively, with an average of 73.30. A SUS score of 73.30 fell into a "good" category with a grade scale of C. Based on the calculation of this SUS score, the system was considered to have good performance. The system had reasonably good usability with room for minor improvements.

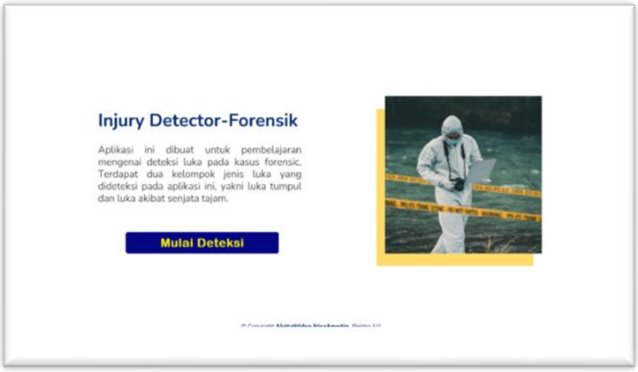

Figure 5. Home page

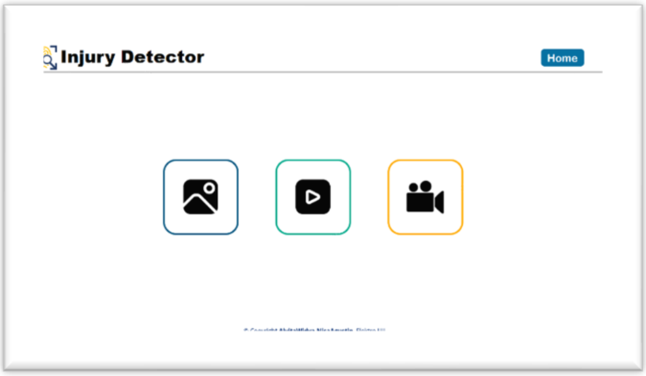

Figure 6. Data input page

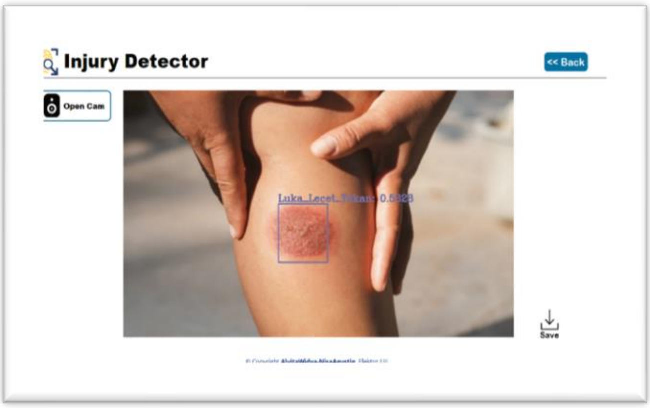

Figure 7. Result Page

CONCLUSIONS

The support of machine learning and deep learning-based models in forensics can help forensic doctors determine the types of wounds and document the visum et repertum (VeR) examination results. It has been demonstrated that machine learning models based on the YOLO algorithm could classify and detect types of wounds with an accuracy of up to 92%. Furthermore, this application received a favorable evaluation with a grade of "C" based on usability testing, indicating that the application can function effectively and is suitable for classifying wound types in forensic medical cases.

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Table 11. Labelling process factors

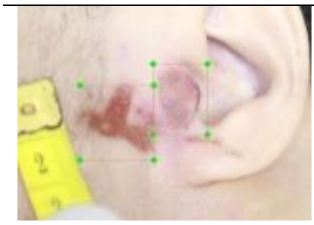
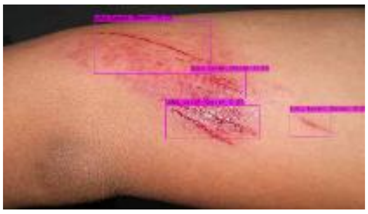
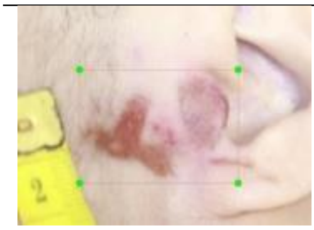
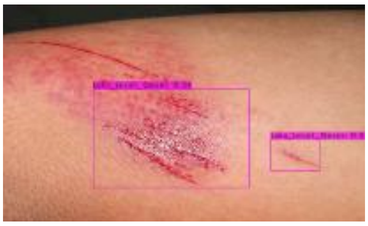
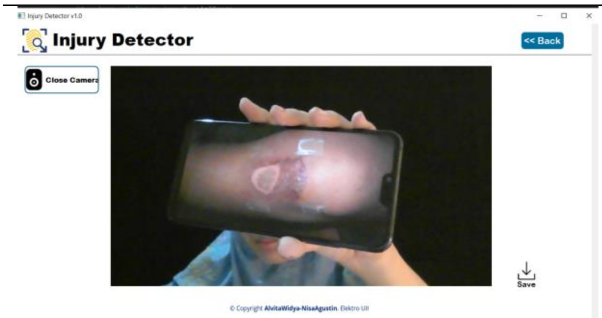
Example Of Labelling Process	**Condition**	**Result Example**	**Condition**
	Detailed		More detected
	Less detailed		Less detected

Table 12. Distance factors

Long-Range	**Close-Range**
	
	

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