ANSYS-Based Simulation and Machine Learning Techniques for Forensic Classification of Knife Wounds

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Received: 3 October 2025 | Revised: 25 October 2025 | Accepted: 4 November 2025

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ABSTRACT

In forensic science, the objective classification of knife-induced injuries is essential for accurately determining the cause and manner of death. Traditional wound analysis often depends on expert judgment, which can be subjective and inconsistent. This paper presents a hybrid framework that combines Finite Element Analysis (FEA) simulations in the Analysis System (ANSYS) with machine learning classifiers in Python to enhance the reliability of forensic wound assessment. Using multilayered tissue models such as skin, fat, and muscle, simulations of stab, incised, and chop wounds were generated under varying knife geometries, insertion angles, and forces. The simulation results, including tissue deformation, stress distribution, and penetration depth, were compiled into a structured dataset. Classifiers such as Logistic Regression (LR), Support Vector Machines (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) were evaluated using 5-fold cross-validation. The RF classifier achieved its best performance with 92% accuracy, 0.92 precision, 0.90 recall, and 0.91 F1-score, demonstrating robustness across wound categories. The confusion matrix confirmed high predictive accuracy for stab and incised wounds, with minor misclassifications between deep incised and light chop injuries caused by feature overlap. The proposed system offers forensic experts an interpretable, scalable, and reproducible framework that connects simulation-based biomechanics with data-driven classification. This research emphasizes the potential of combining simulation and machine learning for evidence-based forensic investigations.

Keywords-knife-induced injuries; forensic analysis; finite element simulation; machine learning; classification; tissue deformation

I. INTRODUCTION

Knife-induced injuries constitute a significant proportion of cases encountered in forensic pathology and medicolegal investigations. Injuries provide insight into the nature and circumstances surrounding an incident, whether resulting from stabbings, incisions, accidents, or acts of violence. Forensic experts depend on wound details to determine the cause and manner of injury. Traditional analysis methods rely on an individual's expertise to make judgments wound. Additionally, no existing tools can accurately assess wound features. Identification of a specific type of knife wound, whether it is a stab, incised, or chop wound, requires a thorough evaluation of factors such as shape, wound depth, and entry type. Wound morphology varies, overlap may exist, and human interpretation is subjective. Hence, in forensic science, it is crucial to enhance the accuracy of systems to improve judgment outcomes.

Forensic investigations usually depend on expert opinions, physical evidence, and descriptive analysis [1, 2]. However, with advances in computing and machine learning, it is now possible to enhance forensic analysis using data-driven methods. In addition to expert judgment for determining wound type, biomedical simulations can also be employed. These simulations can reconstruct an injury pattern identical to a real one [3], helping to identify parameters such as force, stress, tissue response, and more. Forensic software has limitations and cannot fully leverage the predictive power of biomechanical data, leaving a gap in forensic work. This gap can be bridged by using intelligent systems that combine biomechanical simulation with artificial intelligence to enhance the accuracy and reliability of wound analysis. This paper addresses these issues by integrating forensic science with Artificial Intelligence (AI)-based crime analysis and biomedical engineering [4, 5]. It also shows how forensic investigations can shift from guesswork to evidence-based, repeatable analysis through simulations and machine learning. This approach helps forensic teams work more efficiently and improves clarity and accuracy in legal investigations.

This paper addresses these research gaps by:

- Developing a synthetic, labeled dataset of knife-induced injuries through ANSYS simulations.
- Extracting essential biomechanical features such as stress, strain, and force–displacement characteristics.
- Implementing supervised machine learning algorithms in Python for classifying different wound types.
- Establishing a scalable framework to facilitate future research developments in forensic injury modeling and analysis.

II. LITERATURE REVIEW

In forensic science, much focus is placed on sharp force injuries, such as cuts and stab wounds caused by knives or other sharp tools. Stabbing injuries constitute a significant portion of violent crimes and murders worldwide. It is often hard to tell what kind of blade caused the wound, whether it is a kitchen knife, a utility knife, or another sharp tool, because the injuries can appear similar in length, depth, and shape. Traditionally, forensic experts have identified weapon types by visually examining injuries and using tools like X-rays and tissue analysis [6]. However, this method can lead to errors because the skin's elasticity can distort the appearance of wounds. To address these limitations, researchers are now combining artificial intelligence with biomechanical simulations to enhance the objectivity and accuracy of wound classification. Since human muscles are fibrous and offer strong resistance, fat is soft and easily deformed, and skin has high surface strength and elasticity. How these tissues respond to knife injuries depends on their specific material properties [7].

In FEA, these features are crucial for analyzing tissue deformation caused by knife stabs. Complex contact mechanics, including friction, cutting resistance, and energy dissipation, are involved in the interaction between the blade and tissue. It is possible to evaluate force thresholds for penetration, cut progression, and potential wound paths by modeling these interactions using programs such as ANSYS. In biomechanics, finite element analysis is a method for simulating how materials and tissues respond to different forces. ANSYS is useful for modeling knife severance of human tissue because it offers tools for mesh creation, material property definition, and surface interaction simulation [8]. Research has shown that the mechanical response of tissues is significantly affected by factors such as blade type (smooth or serrated), bevel angle, tip sharpness, and insertion speed [9].

According to simulations, energy absorption, penetration depth, and deformation distribution can all serve as measurable characteristics for wound classification. Rich synthetic datasets for machine learning applications can be generated because controlled simulations using FEA would be impossible or unethical in experimental settings involving cadavers or animals. In [10], the authors examined the mechanical properties of soft tissues, noting that skin displays non-linear elastic behavior, especially under tensile and puncture forces. Studies have reported that the Young's Modulus of skin ranges from 0.4 MPa to 0.8 MPa, depending on location and hydration levels. Fat and muscle tissues have much lower moduli but higher Poisson's ratios, suggesting near-incompressibility [11]. Machine learning (ML) is applied in forensic science, especially in pattern recognition and predictive modeling. RF, SVMs, and k-Nearest Neighbors (KNNs) are effectively used to classify injury types, match tool marks, and even identify perpetrators through bite patterns or fingerprints [12-14].

In the context of knife injury classification, ML models can be trained on simulated or real data to predict the type of knife used, the force applied, or the angle of entry based on a set of input features. In [15], the authors demonstrated the feasibility of using Convolutional Neural Networks (CNNs) to analyze wound images. Their dataset consisted of images of incised wounds made with different knife types on synthetic tissues. Support vector machines and decision trees were used to classify injuries based on geometric parameters, including wound width, depth, and edge morphology [16]. These studies show how ML can enable automated analysis of complex forensic data, improve classification accuracy, and reduce the burden on forensic examiners. In cloud forensics research, clustering and machine learning are employed to ensure accuracy and consistency across different environments [17]. The authors in [18] demonstrated that weapon shape influences wound patterns, although forensic wound assessment still relies on expert judgment. This paper addresses this issue using a machine-learning and simulation-based approach.

III. METHODOLOGY

A hybrid, data-driven framework for forensic investigations is developed by integrating ML classifiers with FEA-based biomechanical models. The ethical and financial limitations of cadaver studies are addressed using simulated datasets, which allow precise control over parameters like knife shape, insertion force, tissue type, and penetration angle. This study employed ANSYS to create 3D multilayered human tissue models and to simulate stabbing, incising, and cutting actions with various blades. Python ML classifiers were trained on biomechanical features, including deformation, stress, force, and wound shape, to classify damage type. Python was used for data extraction, analysis, and classification alongside finite element simulations with the Explicit Dynamics module of ANSYS Workbench 2023 R2. This hybrid workflow enabled a scalable, repeatable, and efficient forensic injury investigation system. This section presents the simulation parameters, material properties, and model validation steps.

A. Simulation Design and Parameters

Three knife types were included: Paring, Chef, and Utility. Insertion angles were 30°, 45°, 60°, and 90°. The applied loading levels were 5, 20, and 30 N, corresponding to the force/displacement inputs. Tissue layers tested included Fat, Muscle, and Bone. Each knife–tissue setup was evaluated under impact and gradual loading conditions, yielding 500 simulation cases in total. The mesh was composed of tetrahedral elements with an average size of 1.0 mm, locally refined to 0.5 mm near the knife–tissue contact area. Mesh convergence analysis confirmed that the variation in peak stress was less than 3% between successive test refinements. The bottom surface of the tissue model was fixed in all degrees of freedom to replicate anatomical support, while the lateral faces remained free. Contact between the knife and tissue was defined as surface-to-surface contact, using a Coulomb friction coefficient of 0.35. This was implemented through a penalty-based contact formulation with minor stabilization to ensure numerical stability and convergence. The simulations employed an explicit transient solver with adaptive time-stepping to effectively capture stress-wave propagation and deformation during penetration. Figure 1 displays the simulated tissue response to stabbing, incision, and chopping.

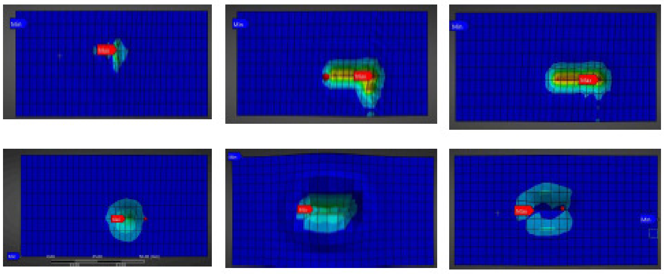

Fig. 1. Simulated tissue response to stabbing, incision, and chopping.

B. Material Properties

Material models were characterized as linear isotropic elastic, with properties summarized in Table I. These parameters were chosen based on published biomechanical studies on soft tissue mechanics [7, 10, 11]. A comparative benchmarking of simulated stress and deformation responses against the experimental findings of [6] and [9] confirmed that the stress values (0.4–56 MPa) and penetration depths (5–36 mm) fall within the reported experimental ranges. Table II shows the material properties used for the Finite Element Analysis, including Young's Modulus, Poisson's Ratio, and Density values for each tissue or knife material. The Notes column provides modeling assumptions, while the References column cites literature sources for the material parameters considered.

C. Model Validation and Benchmarking

Finite element simulations for stress and deformation outputs were compared with existing experimental and FEA studies on knife–tissue interaction. Simulated maximum stress, which ranged from 0.4 to 56 MPa, and penetration depths from 5 to 36 mm closely matched the ranges reported by [6] and [9] for different knife geometries and soft tissue types. Mesh convergence tests showed less than 3% variation in peak stress with mesh refinement from 1.0 mm to 0.5 mm near the contact zone, confirming numerical stability. Therefore, the results from the ANSYS model accurately represent knife tissue mechanics, and these findings can be used to generate synthetic wound features for machine learning classification.

TABLE I. KNIFE PROPERTIES

Parameter	Paring knife	Chef's knife	Utility knife
Blade length	90 mm	200 mm	60 mm (exposed portion)
Blade width	24 mm	45 mm (widest point)	18 mm
Blade thickness	2 mm - 0.45 mm (tapered)	2.5 mm - 0 mm (tapered)	0.6 mm (uniform)
Blade shape	Tapered tip	Curved with pointed tip	Trapezoidal, straight edge

TABLE II. MATERIAL PROPERTIES FOR FEA

Material	Young's modulus MPa	Poisson's ratio	Density kg/m³	Notes	Reference
Skin	0.6	0.48	1100	Elastic, high surface strength	[10]
Fat	0.03	0.49	920	Soft, easily deformed	[7]
Muscle	0.3	0.45	1040	Fibrous, more resistant than fat	[11]
Steel (Knife)	200,000	0.30	7850	Used for a rigid or deformable knife	Standard structural steel

IV. RESULTS AND DISCUSSION

A. Dataset Description and Preprocessing

The dataset contains 500 samples. Key features are Knife Type, Angle, Force/Displacement, Type, Max Deformation, Max Stress, Wound Shape, Class, Knife Material, Tissue Type, and Injury Type. The target variable is Class. Numerical features such as Angle, Max Stress, and Force/Displacement were normalized using Min–Max scaling to keep values within the [0,1] range. Categorical variables, including Knife Type, Knife Material, Tissue Type, and Injury Type, were encoded with One-Hot Encoding to convert non-numeric data into a binary format. Missing values were filled with the median. Label encoding was applied to the target variable to represent wound types as integer classes. The dataset is balanced across three classes: stab, incised, and chopped.

B. Model Training and Evaluation

The dataset was partitioned into training (70%) and testing (30%) subsets. Four supervised machine learning algorithms (LR, SVM, RF, and XGBoost) were employed in Python utilizing scikit-learn and XGBoost libraries. The objective was to categorize wound types (stab, incised, chopped) based on mechanical and geometric features extracted from ANSYS simulations.

C. Hyperparameter Tuning

Hyperparameters were optimized using 5-fold cross-validation (CV) on the training set. Grid search procedures explored the following ranges:

- Random Forest: n estimators = $[100, 200, 300]$, max depth = $[none, 5, 10]$, min samples split = $[2, 5]$
- SVM: $C = [0.1, 1, 10]$, kernel = $[linear, rbf]$

- XGBoost: learning rate = $[0.01, 0.1]$, n estimators = [50, 100, 200], max depth = [3, 5, 7]
- Logistic Regression: $C = [0.01, 0.1, 1, 10]$

Cross-validation outcomes were documented as mean ± standard deviation to reflect the model's stability across different folds.

TABLE III. FOLD CROSS-VALIDATION (CV) AND TEST SET RESULTS FOR ALL CLASSIFIERS

Model	CV Accuracy (mean ± SD)	CV Precision (mean ± SD)	CV Recall (mean ± SD)	CV F1 (mean ± SD)	Test Accuracy
LR	0.83 ± 0.04	0.81 ± 0.03	0.79 ± 0.04	0.80 ± 0.03	0.83
SVM	0.87 ± 0.03	0.86 ± 0.03	0.84 ± 0.03	0.85 ± 0.03	0.87
XGBoost	0.89 ± 0.03	0.88 ± 0.03	0.87 ± 0.03	0.87 ± 0.03	0.89
RF	0.92 ± 0.02	0.92 ± 0.02	0.90 ± 0.03	0.91 ± 0.02	0.92

D. *Model Performance and Interpretation*

Among the four models, the RF Classifier achieved the best overall performance with 92 % accuracy, 0.92 precision, 0.90 recall, and 0.91 F1-score on the test set (Table III). The confusion matrix in Figure 2 demonstrates strong class-wise performance, particularly for stab and incised wounds, with minor overlap between deep incised and light chop injuries due to feature similarity in deformation and stress levels. The confusion matrix given in Figure 2 further confirmed the model's robustness, showing strong diagonal dominance and minimal off-diagonal misclassifications.

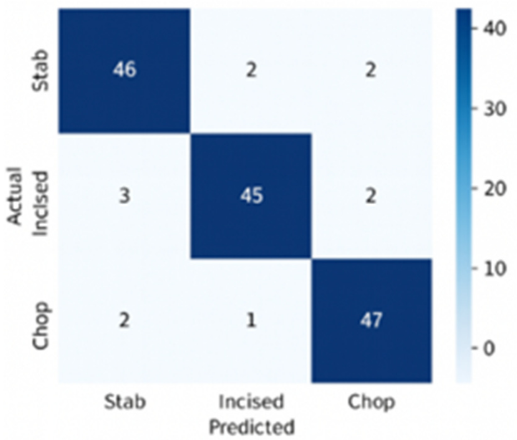

Fig. 2. Confusion matrix.

The feature-importance score shown in Figure 3 indicates that angle, loading type (gradual/impact), and maximum stress are the most significant features. Therefore, both mechanical and geometric parameters contribute to differentiating wound categories.

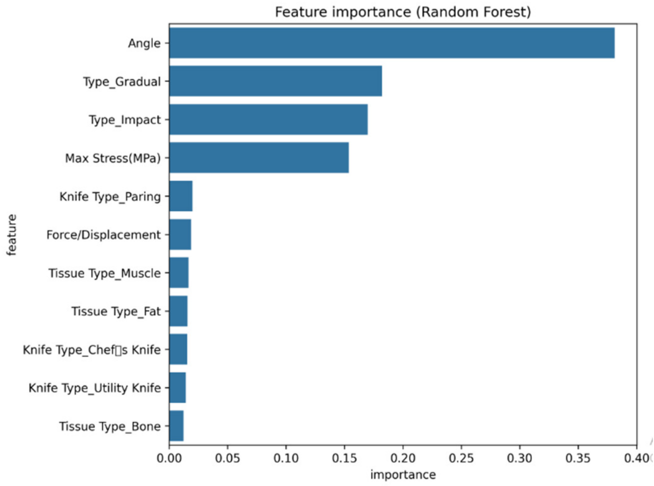

Fig. 3. Feature importance score.

E. *Statistical Significance and Error Analysis*

To check reliability of classification results, statistical significance tests and error analysis was carried out. A one-way Analysis of Variance (ANOVA) was applied to compare the 5-fold cross-validated accuracies of all four models. LR, SVM, XGBoost, and RF, to determine whether observed differences in mean performance were statistically meaningful. The results of the ANOVA test showed substantial difference among model performances ($p < 0.05$). The RF classifier is superior to LR and SVM, with $p < 0.05$ in post-hoc pairwise comparisons using Tukey's Honest Significant Difference (HSD) test. Difference between RF and XGBoost was not statistically significant since $p > 0.05$. RF model has better performance.

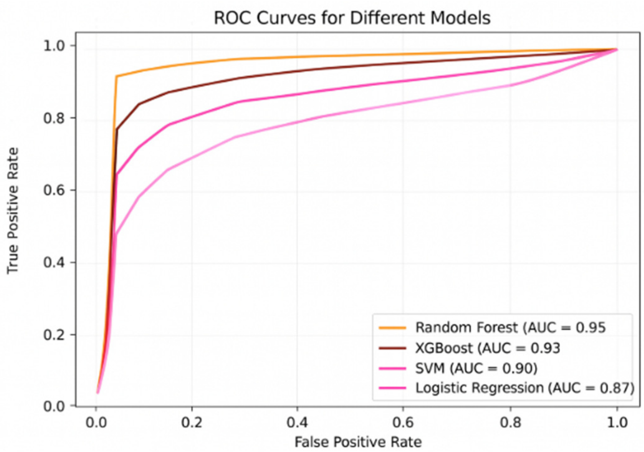

Fig. 4. ROC curves for all models.

All models' Receiver Operating Characteristic (ROC) curves are displayed in Figure 4, which clearly illustrates the separation between positive and negative class probabilities. To assess each classifier's ability to distinguish among the three injury categories (stab, incised, and chopped), ROC curves were generated for each model using a one-vs-rest approach, as shown in Figure 4. The resulting Area Under the Curve (AUC) values were: RF = 0.95, XGBoost = 0.93, SVM = 0.90, and LR = 0.87. Their higher AUC scores further support the superior discrimination ability of RF and XGBoost. A slight overlap was observed between deep incised and mild chopped wounds due to their similar deformation and stress characteristics, although most stab and incised injuries were accurately classified. Precision and recall remained balanced across all categories.

V. DISCUSSION AND FORENSIC IMPLICATIONS

This work models soft tissue as homogeneous and linearly elastic, without considering anisotropy, vascularization, or viscoelasticity. It omits bone architecture and complex border interactions, which could influence stress distribution and wound shape, though these could be added in future research for greater physiological accuracy. Incorporating postmortem imaging data could also improve the model's applicability. Future studies might include 3D reconstructions of wound shapes from postmortem CT or MRI scans for direct comparison with simulated injuries. Additionally, the framework could be expanded to include a range of blunt and sharp weapons, helping forensic experts develop predictive databases of wound signatures under controlled mechanical conditions.

VI. REPRODUCIBILITY AND COMPUTATIONAL ENVIRONMENT

The Explicit Dynamics module in ANSYS Workbench 2023 R2 was utilized for all finite-element simulations to analyze transient knife–tissue interactions. To achieve accurate dynamic responses, each simulation used adaptive time stepping and a tetrahedral mesh with an average element size of 1 mm, refined to 0.5 mm in the contact zone. Employing penalty-based contact enforcement, the solver applied a Coulomb friction coefficient of 0.35 to model the interaction between the knife and tissue.

The following Python libraries were used to implement the machine learning experiments:

- "*scikit-learn*" for Model development, cross-validation, and evaluation
- "*numpy*" for data preprocessing and feature handling
- "*matplotlib*" and "*seaborn*" for visualization of ROC curves, feature importance, and confusion matrix.

VII. CONCLUSION AND FUTURE SCOPE

This paper combines machine learning methods for forensic injury diagnosis with biomechanical simulations in ANSYS. The ANSYS interface was used to define tissue properties and simulate knife interactions under different conditions. Python was employed to clean data, train the model, and generate predictions. A Random Forest (RF) classifier is used to accurately classify wound types. Together, these tools demonstrate that integrating simulation and machine learning can be an effective approach for classifying forensic injuries. This provides forensic experts with a methodology for identifying injuries caused by knives. Future research can expand on this by using a diverse dataset, including real-world forensic cases, and by employing deep learning models.

DATA AVAILABILITY

Data will be made available upon request

REFERENCES

[1] J. N. Muqadas, N. U. Aien, T. Fatima, and M. A. Ansari, "Crime scene to judgment: A review on identifying gaps in crime scene investigation and implementing solutions," *Forensic Insights and Health Sciences Bulletin*, vol. 3, no. 1, pp. 1–6, Apr. 2025.

[2] L. Bhoyar and B. Srivastava, "Revolutionizing forensic investigations through AI-driven pollen analysis: A narrative review," *Review of Palaeobotany and Palynology*, vol. 344, Jan. 2026, Art. no. 105440, https://doi.org/10.1016/j.revpalbo.2025.105440.

[3] S. Ziogos, K. Pitts, A. R. Dempsey, I. R. Dadour, and P. A. Magni, "Overview of Sharp Force Damage: Key Factors, Analytical Approaches, Reconstruction Methods, and Future Directions for Standardization in Forensic Investigations," *WIREs Forensic Science*, vol. 7, no. 2, p. e70012, June 2025, https://doi.org/10.1002/wfs2.70012.

[4] R. Morán-Torres, K. Feld, J. Hesser, Y. M. Taalab, and K. Yen, "Artificial intelligence and computer vision in forensic sciences," *Rechtsmedizin*, vol. 35, no. 4, pp. 219–225, Aug. 2025, https://doi.org/10.1007/s00194-025-00775-3.

[5] K. B. Kalinowska *et al.*, "A machine learning approach for automated injuries classification on postmortem images," *Journal of Forensic and Legal Medicine*, vol. 115, Oct. 2025, Art. no. 102955, https://doi.org/10.1016/j.jflm.2025.102955.

[6] L. Bergman, F. Brock, and D. Errickson, "Use of different imaging techniques in stab wound analysis," *Science & Justice*, vol. 64, no. 1, pp. 50–62, Jan. 2024, https://doi.org/10.1016/j.scijus.2023.11.002.

[7] G. Singh and A. Chanda, "Mechanical properties of whole-body soft human tissues: a review," *Biomedical Materials (Bristol, England)*, vol. 16, no. 6, Oct. 2021, https://doi.org/10.1088/1748-605X/ac2b7a.

[8] D. Nath, Ankit, D. R. Neog, and S. S. Gautam, "Application of Machine Learning and Deep Learning in Finite Element Analysis: A Comprehensive Review," *Archives of Computational Methods in Engineering*, vol. 31, no. 5, pp. 2945–2984, July 2024, https://doi.org/10.1007/s11831-024-10063-0.

[9] V. Vachirawongsakorn, J. Painter, and N. Márquez-Grant, "Knife cut marks inflicted by different blade types and the changes induced by heat: a dimensional and morphological study," *International Journal of Legal Medicine*, vol. 136, no. 1, pp. 329–342, Jan. 2022, https://doi.org/10.1007/s00414-021-02726-5.

[10] A. Kalra, A. Lowe, and A. M. Al-Jumaily, "Mechanical Behaviour of Skin: A Review," *Journal of Material Science & Engineering*, vol. 5, no. 4, 2016, Art. no. 1000254, https://doi.org/10.4172/2169-0022.1000254.

[11] M. Takaza, K. M. Moerman, and C. K. Simms, "Passive skeletal muscle response to impact loading: Experimental testing and inverse modelling," *Journal of the Mechanical Behavior of Biomedical Materials*, vol. 27, pp. 214–225, Nov. 2013, https://doi.org/10.1016/j.jmbbm.2013.04.016.

[12] F. Oladipo, E. Ogbuju, F. S. Alayesanmi, and A. E. Musa, "The State of the Art in Machine Learning-Based Digital Forensics." Social Science Research Network, Rochester, NY, May 18, 2020, https://doi.org/10.2139/ssrn.3668687.

[13] F. K. H. Mihna, M. A. Habeeb, Y. L. Khaleel, Y. H. Ali, and L. A. E. Al-saeedi, "Using Information Technology for Comprehensive Analysis and Prediction in Forensic Evidence," *Mesopotamian Journal of CyberSecurity*, vol. 4, no. 1, pp. 4–16, Mar. 2024, https://doi.org/10.58496/MJCS/2024/002.

[14] A.-I. Piraianu *et al.*, "Enhancing the Evidence with Algorithms: How Artificial Intelligence Is Transforming Forensic Medicine," *Diagnostics*, vol. 13, no. 18, Jan. 2023, Art. no. 2992, https://doi.org/10.3390/diagnostics13182992.

[15] S.-T. Huang *et al.*, "Deep Learning-Based Clinical Wound Image Analysis Using a Mask R-CNN Architecture," *Journal of Medical and*

Biological Engineering, vol. 43, no. 4, pp. 417–426, Aug. 2023, https://doi.org/10.1007/s40846-023-00802-2.

[16] Z. Li, P. Liu, W. Wang, and C. Xu, "Using support vector machine models for crash injury severity analysis," *Accident Analysis & Prevention*, vol. 45, pp. 478–486, Mar. 2012, https://doi.org/10.1016/j.aap.2011.08.016.

[17] R. Al-mugern, S. H. Othman, and A. Al-Dhaqm, "An Improved Machine Learning Method by applying Cloud Forensic Meta-Model to Enhance the Data Collection Process in Cloud Environments," *Engineering, Technology & Applied Science Research*, vol. 14, no. 1, pp. 13017–13025, Feb. 2024, https://doi.org/10.48084/etasr.6609.

[18] Y. Singi, D. Dabhi, N. Nagar, and J. Jain, "Patterned injuries from a modified sickle: Forensic observations and insights-Case report," *SAGE open medical case reports*, vol. 13, 2025, Art. no. 2050313X251365464, https://doi.org/10.1177/2050313X251365464.