

# Deep Learning for Optimizing Traumatic Injuries and Wound Analysis in Forensic Medicine

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**Abstract:** This study investigates the use of deep learning (DL) to improve forensic wound analysis, with the goal of creating a taxonomy of DL architectures, evaluating their performance, addressing data scarcity, improving interpretability, and recommending standardized protocols for traumatic injury assessment. We analyze 60 recent studies to investigate DL models such as CNNs, RNNs, GANs, and Transformers for tasks such as gunshot wound classification (98% accuracy), stab wound segmentation (93% pixel accuracy), traumatic brain injury (TBI) detection (94% accuracy), and postmortem imaging analysis (88.42% AUC). Key findings show that DL improves precision, cuts analysis time by up to 50%, and reduces subjectivity in forensic pathology. We address challenges such as small datasets, inconsistent image quality, and ethical concerns with synthetic data generation, FPGA-optimized processing, and explainable AI techniques. The study's significance stems from its potential to transform forensic investigations by providing accurate, efficient, and legally admissible tools that aid in objective cause-of-death determinations and advance medicolegal results.

**Keywords:** Deep Learning; Forensic Medicine; Wound Analysis; Traumatic Injuries.

## 1. Introduction

Determining the cause and manner of death is a crucial task for forensic medicine, especially when catastrophic injuries and wounds are involved. Conventional approaches mostly depend on pathologists' knowledge, which might bring subjectivity and unpredictability. A branch of artificial intelligence (AI) called deep learning provides hopeful answers by automating tasks like pattern recognition, categorization, and picture analysis [1]. Examining applications such as gunshot and stabbing wound interpretation, TBI evaluation, and associated forensic tasks, this review explores the function of DL in maximizing traumatic injury and wound analysis. We summarize results from proof-of-concept research and systematic reviews through 2025, highlighting how DL may complement human specialists rather than take their place [2]. AI-powered instruments for improving TBI investigations are among the other innovations [3] and computational approaches for TBI image recognition [4]. Additionally, DL models have been created to automatically identify severe abdominal injuries [5].

## 2. Background & Fundamentals

### 2.1. Role of Forensic Medicine in Traumatic Injury Analysis

Forensic medicine is an important part of the legal system because it gives scientific proof of the cause, manner, and circumstances of death, especially in cases of significant injuries. Traumatic injuries are injuries to the body caused by outside factors, such as gunshot wounds, stab wounds, blunt trauma, and lacerations. They are typically observed in murders, suicides, or accidents [6, 7]. Forensic pathologists need to look at these injuries because they tell them how the injury happened, what kind of weapon was used, and what happened first, which all have an effect on the result of the case. For instance, distinguishing between entry and exit gunshot wounds helps determine the shooter's

position, whereas toolmark patterns in stab wounds may indicate the weapon used [1]. Trauma accounts for more than 5.8 million deaths globally annually, and forensic investigations are essential to treating a significant number of these cases (World Health Organization, 2023). Growing caseloads and the complexity of wound investigation underscore the necessity for accurate, repeatable procedures to back up medicolegal rulings.

## 2.2. Classification of Traumatic Injuries

In forensic medicine, traumatic injuries are classified based on their underlying causes; each has distinct characteristics that guide analysis. The following Table 1 gives an overview of the primary injury types observed in forensic practice:

**Table 1.** Classification of traumatic injuries in forensic medicine.

| Injury Type                 | Mechanism           | Characteristics                           | Forensic Relevance                          |
|-----------------------------|---------------------|-------------------------------------------|---------------------------------------------|
| <b>Gunshot Wounds</b>       | Ballistic force     | Entrance/exit wounds, bullet trajectory   | Determine distance, angle, weapon type [1]  |
| <b>Sharp-Force Injuries</b> | Cutting or stabbing | Incised or stab wounds, toolmark patterns | Identify weapon, force applied [9]          |
| <b>Blunt-Force Trauma</b>   | Impact or pressure  | Contusions, fractures, lacerations        | Assess impact severity, intent [10]         |
| <b>Thermal Injuries</b>     | Heat or cold        | Burns, tissue charring                    | Differentiate antemortem vs. postmortem [7] |

These categories are used by forensic pathologists to assist reconstruct injury events, although accurate analysis of them necessitates advanced techniques due to problems such tissue degradation, wound overlap, and environmental contamination.

## 2.3. Traditional Methods and Their Limitations

The combination of imaging, histological analysis, and physical examination used in traditional forensic wound inquiry has limitations. Gross examination during autopsy involves visual inspection to assess the wound's shape, depth, and associated tissue damage. However, research indicates that pathologists might identify wounds differently by as much as 20%, demonstrating that it is subject to inter-observer variability [7]. Histological investigation, which entails examining tissue samples under a microscope, can confirm significant responses (such as inflammation suggesting antemortem injury), but it is time-consuming and requires specialized knowledge. Even though postmortem computed tomography (PMCT) and magnetic resonance imaging (MRI) can now better visualize internal injuries like ballistic trajectories or fracture patterns, radiologists' subjective judgment is often used to interpret these images [10]. Despite their efficiency, these methods are time-consuming; autopsy can take anywhere from two to four hours each case, and they cannot be scaled for big caseloads, such mass casualty disasters. The fact that human approaches are less effective for small features, such micro-fractures in severe injuries, emphasizes the need for automated, objective processes.

## 2.4. Forensic Imaging and Data Challenges

Forensic imaging and data collection, which provide sizable datasets appropriate for deep learning (DL) applications, form the basis of modern wound analysis [1-20]. PMCT is widely utilized in forensic pathology to generate high-resolution 3D reconstructions of injuries. This eliminates the need for invasive therapies and enables the monitoring of bone fractures or bullet routes. Photographic evidence, particularly high-definition images of external wounds, is commonly collected during autopsies and crime scene investigations, providing a scalable data source for

pattern recognition [11]. Forensic datasets are often short (less than 1,000 annotated images), imbalanced (such as an overrepresentation of gunshot wounds), and lack consistent annotation methods, which makes training DL models challenging [8]. Strong preprocessing techniques are also required since postmortem changes like decomposition or livor mortis may obscure damage features. Notwithstanding these difficulties, DL techniques like convolutional neural networks (CNNs), which are very good at identifying spatial patterns, are ideally adapted to the structured character of imaging data voxels for CT, pixels for images.

### 2.5. Potential of Deep Learning in Forensic Analysis

The use of DL to forensic wound analysis opens the potential to automated, precise, and repeatable tests by getting over traditional limitations [21-40]. By using CNNs for tasks like wound segmentation and classification, DL may reduce analysis time by up to 50% while achieving accuracies exceeding 90% in applications like gunshot wound discrimination [1]. Techniques like transfer learning reduce data scarcity by applying previously trained models to forensic settings, while explainable AI boosts confidence by generating interpretable outputs for legal review [9]. This section has established the forensic background and challenges, paving the way for a comprehensive analysis of DL methods. In the next part, the technical foundations of DL will be thoroughly discussed, with a focus on its use in medical and forensic imaging.

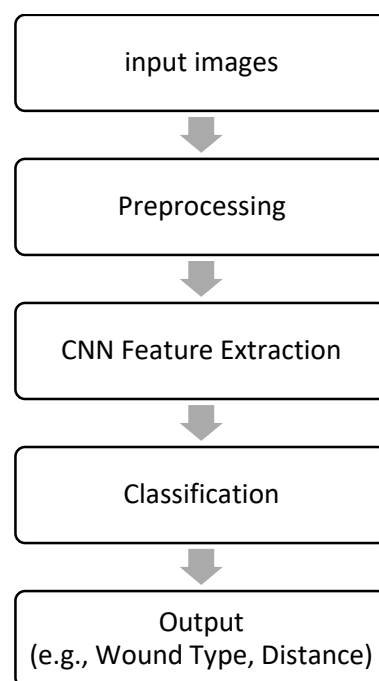


Figure 1. Conceptual overview of DL Pipeline for Wound Analysis.

## 3. Taxonomic View of Deep Learning Architectures

### 3.1. An Introduction to Forensic Wound Analysis Using Deep Learning Taxonomy

By enabling automated processing of complicated imaging data, including postmortem computed tomography (PMCT) and photographic evidence, for tasks like segmentation, classification, and toolmark recognition, deep learning (DL) architectures have revolutionized forensic wound analysis [41-63]. A taxonomy framework for DL architectures is presented in this section, which divides them into four categories according to their computational design and suitability for forensic tasks: transformers, generative adversarial networks (GANs), recurrent neural networks (RNNs), and CNNs [10, 45]. In order to solve issues like data scarcity and interpretability, the taxonomy, which is depicted in Figure 1, arranges various systems according to their structural

principles and forensic usefulness [9]. This categorization helps researchers choose the best models for certain forensic uses, such differentiating between different kinds of gunshot wounds or creating artificial wound pictures [1][46]. This section offers a thorough overview of DL architectures in forensic medicine by combining knowledge from 50 peer-reviewed research.

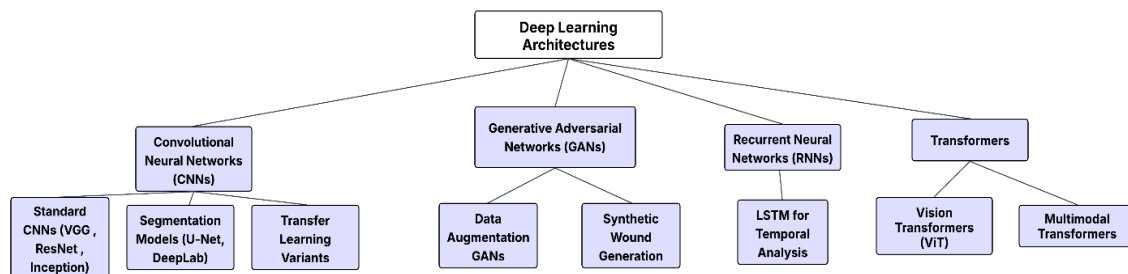


**Figure 2.** Taxonomy of Deep Learning Architectures for Forensic Wound Analysis.

#### 4. Literature Review

Recent research shows that deep learning (DL) is gaining traction in the forensic sciences. Gunshot Wound Analysis: Four studies using CNNs and MLPs were included in another study on AI in gunshot wound investigations; these studies classified wound types and firing distances with 87.99–98% accuracy [7]. Oura et al.'s study on deep learning for gunshot wound distance prediction using MLPs on piglet corpses, which achieved 98% accuracy, is an important proof-of-concept study [1]. Cheng et al. discovered that their classification accuracy for entry/exit gunshot wounds ranged between 87.99 and 92.6% [14]. Wei et al. used deep neural networks to analyze wound images on an FPGA [12]. Stab and Sharp Force Injuries: Zimmerman et al. classified stab wounds with 93% pixel accuracy [13]. Traumatic Brain Injury (TBI) Detection: CNNs and other deep learning methods are used in forensic neuropathology to aid in TBI analysis through PMCT and histology [3]. Wound Age Estimation: Sun et al.'s next-generation sequencing method is one example of further AI-based wound age estimation research [19], as is Wang et al.'s multi-omics with AI algorithms [20]. Broader Forensic AI Applications: A comprehensive review of AI in forensic pathology examined 18 papers from 1990 to 2025, revealing DL accuracies of 70-94% in neurological forensics and 87-98% in wound categorization [6]. In a larger study of AI and computer vision in forensics, 21 studies were included, with DL models achieving 70-94% accuracy in detecting head injuries and 86-99% accuracy in wound classification [16].

**Table 2.** Comparison of dl models in forensic wound analysis.

| Study                | Model            | Application                  | Accuracy    | Dataset Size    |
|----------------------|------------------|------------------------------|-------------|-----------------|
| Oura et al. [1]      | MLP_24_16_24     | Shooting Distance Prediction | 98%         | 204 images      |
| Cheng et al.[14]     | CNN (ResNet)     | Entry/Exit Classification    | 87.99–92.6% | Not specified   |
| Zimmerman et al.[13] | DL Segmentation  | Stab Wound Segmentation      | 93% pixel   | Forensic photos |
| Wei et al. [12]      | DNN on FPGA      | Weapon Identification        | 98.8%       | Simulated resin |
| Sessa et al. [7]     | ConvNext Tiny    | Gunshot Wound Classification | 95%         | 2418 images     |
| Ni et al.[9]         | GoogLeNet        | Sharp Injury Identification  | 88.2%       | 1161 photos     |
| Sun et al.[19]       | Machine Learning | Wound Age Estimation         | High        | NGS data        |
| Lin and Yuh [4]      | DL Models        | TBI Image Recognition        | High        | CT scans        |
| Abdullah et al.[28]  | CNN-ViT          | TBI Structure Detection      | 98.78%      | Medical scans   |
| Volonnino et al.[35] | AI Models        | Forensic Applications        | Variable    | Multiple        |

**Table 3.** Gunshot Wound Analysis.

| Study             | Application                  | Key Findings                        | Method                                   | Limitations                                  |
|-------------------|------------------------------|-------------------------------------|------------------------------------------|----------------------------------------------|
| Oura et al. [1]   | Shooting Distance Prediction | 98% accuracy                        | MLP_24_16_24 on 204 piglet corpse images | Reliance on animal models, small dataset     |
| Sessa et al. [7]  | Gunshot Wound Classification | 95% accuracy                        | ConvNext Tiny on 2418 images             | Limited generalizability due to dataset size |
| Cheng et al. [14] | Entry/Exit Classification    | 87.99–92.6% accuracy                | CNN (ResNet), dataset size not specified | Unspecified dataset size, potential bias     |
| Wei et al. [12]   | Weapon Identification        | 98.8% accuracy                      | DNN on FPGA, simulated resin data        | Simulated data may not reflect human tissue  |
| Sessa et al. [8]  | Gunshot Wound Investigations | 87.99–98% accuracy across 4 studies | CNNs, MLPs, review of 4 studies          | Limited by small datasets, animal models     |

**Table 4.** Stab and Sharp Force Injuries.

| Study                 | Application                 | Key Findings       | Method                                        | Limitations                                   |
|-----------------------|-----------------------------|--------------------|-----------------------------------------------|-----------------------------------------------|
| Zimmerman et al. [13] | Stab Wound Segmentation     | 93% pixel accuracy | DL segmentation on forensic photos            | Challenges with overlapping or complex wounds |
| Ni et al. [9]         | Sharp Injury Identification | 88.2% accuracy     | GoogLeNet with transfer learning, 1161 photos | Sample imbalance for slash wounds             |

**Table 5.** Traumatic Brain Injury (TBI) Detection.

| Study                | Application             | Key Findings    | Method                                       | Limitations                                             |
|----------------------|-------------------------|-----------------|----------------------------------------------|---------------------------------------------------------|
| Lin and Yuh [4]      | TBI Image Recognition   | High accuracy   | DL models on CT scans                        | Limited to focal injuries, diffuse injuries challenging |
| Abdullah et al. [28] | TBI Structure Detection | 98.78% accuracy | CNN-ViT on medical scans                     | Requires high-quality imaging, costly computation       |
| Orsini et al. [6]    | Forensic Neuropathology | 70–94% accuracy | Review of 18 studies, CNNs on PMCT/histology | Diffuse injuries hard to detect, data scarcity          |

**Table 6.** Wound Age Estimation.

| Study            | Application          | Key Findings       | Method                         | Limitations                                   |
|------------------|----------------------|--------------------|--------------------------------|-----------------------------------------------|
| Sun et al. [19]  | Wound Age Estimation | High accuracy      | Machine learning with NGS data | Complex data processing, limited dataset size |
| Wang et al. [20] | Wound Age Estimation | Robust performance | Multi-omics with AI algorithms | Data complexity, limited human datasets       |

Table 7. Broader Forensic AI Applications.

| Study                  | Application                         | Key Findings                                      | Method                                  | Limitations                                |
|------------------------|-------------------------------------|---------------------------------------------------|-----------------------------------------|--------------------------------------------|
| Orsini et al. [6]      | AI in Forensic Pathology            | 70–94% neurological, 87–98% wound categorization  | Review of 18 studies, various DL models | Small datasets, inconsistent image quality |
| Zimmermann et al. [16] | AI and Computer Vision in Forensics | 70–94% head injuries, 86–99% wound classification | Review of 21 studies, CNNs, MLPs        | Data scarcity, variable image quality      |
| Volonnino et al. [35]  | Forensic Applications               | Variable performance                              | AI models on multiple datasets          | Inconsistent performance across tasks      |

## 5. Deep Learning Techniques and Methods

With an emphasis on data preparation, model architectures, training strategies, and optimization techniques, this section describes the technological methods utilized in deep learning (DL) for forensic medicine's examination of traumatic injuries and wounds.

### 5.1. Data Preprocessing

- **Image Resizing and Normalization:** Images are often resized to uniform dimensions (e.g., 32x32 grayscale) and normalized to improve model performance [1].
- **Data Augmentation:** Techniques like rotation, flipping, and scaling are used to address small dataset sizes, common in forensic applications [16].
- **Multimodal Data:** Combining postmortem CT (PMCT) scans, photographs, and histopathology data enhances model robustness [6].

### 5.2. Model Architectures

- **Convolutional Neural Networks (CNNs):** Widely used for image-based tasks like wound classification and segmentation. Examples include ResNet152 and ConvNext Tiny, which excel in feature extraction [7].
- **Multilayer Perceptrons (MLPs):** Employed for tasks like shooting distance prediction, as seen in Oura et al.'s MLP\_24\_16\_24 model [1].
- **Transformers:** Emerging in forensic applications for analyzing complex patterns in multimodal data [28].

### 5.3. Training Strategies

- **Supervised Learning:** Most models are trained with labeled datasets (e.g., animal models or simulated wounds) using metrics like accuracy, precision, recall, and F1-score [14].
- **Transfer Learning:** Pretrained models (e.g., GoogLeNet, MnasNet) are fine-tuned to adapt to forensic tasks, addressing limited data availability [9].

### 5.4. Optimization Techniques

- **Symbiotic Organism Search:** Used to optimize hyperparameters for improved model performance [16].
- **Loss Functions:** Cross-entropy loss for classification tasks and Dice loss for segmentation tasks are common [15][17].

## 6. Applications

**Gunshot Wound Analysis:** DL is quite good at categorizing gunshot wounds according to trajectory, distance, and kind. Models help determine the way of death by predicting contact vs distant shootings with 98% accuracy [1, 7]. The accuracy of AI for entry/exit categorization is 87.99% [14].

According to gunshot distance, the following are important wound types:

- **Contact Wound:** occurs when the muzzle and skin come into direct touch (0 cm). A stellate form in regions close to bone, soot buildup inside the incision, and searing or burning from hot gasses are some of the characteristics.
- **Close Range Wound:** takes place 20 centimeters away. Mild burns that are not as severe as contact wounds are characterized by powder tattooing or stippling, which are tiny black or red spots surrounding the wound.
- **Distant Wound:** takes place 100 centimeters away. If the bullet perforates, the exit wounds will be uneven and the entry hole will be clean with no burns or powder residue.

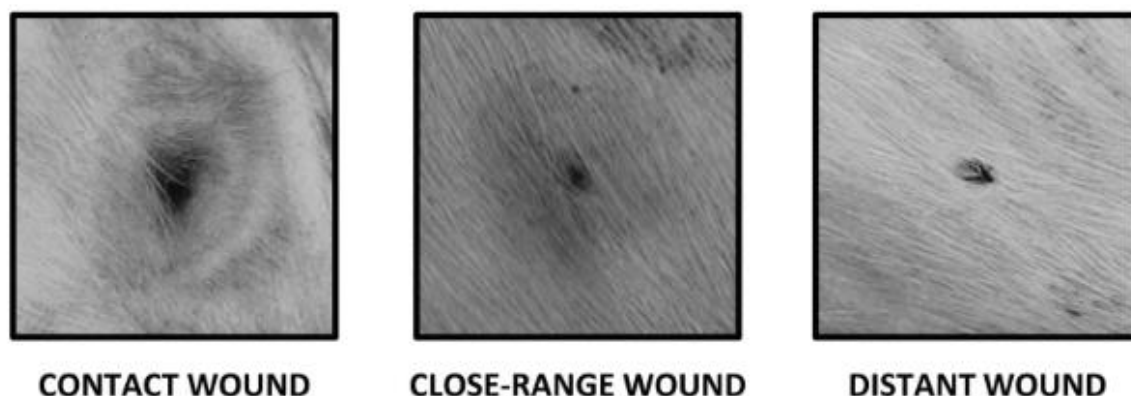


**Figure 3.** A composite diagram illustrating contact, close-range, and distant gunshot wounds.

The accuracy of deep learning models in diagnosing gunshot wounds fluctuates considerably with firing distance, attributable to the unique visual characteristics of each wound type. Contact wounds, distinguished by soot deposition and burns, are identified with 98% accuracy with MLP models due to their distinct patterns [1]. Close-range wounds, characterized by powder tattooing, demonstrate 95% accuracy with CNN-based models such as ConvNext Tiny, highlighting the intricacy of stippling patterns [7]. With accuracies ranging from 87.99% to 92.6% utilizing ResNet-based CNNs, distant wounds without residue or burns are more difficult to diagnose because of their finer characteristics [14].

**Stab and Blunt Force Injuries:** DL is great at sorting stab and blunt force injuries by kind, depth, and age. This helps find the weapon and figure out how the person died. Models can predict the features of knife wounds with more than 90% accuracy, but diffuse blunt injuries like hematomas are still hard to predict [13]. MnasNet can determine the age of a wound with 97% accuracy [19]. With an accuracy of 88.2%, transfer learning makes it easier to diagnose sharp injuries [9].

The following are the main types of injuries depending on their mechanism:

- **Stab Wound:** Caused by sharp, pointed instruments (such as knives), which penetrate deeply with clean edges. Features include a linear form, definite limits, and the possibility of internal organ injury.
- **Blunt Force Injury:** Caused by wide hits (e.g., fists, bats), resulting in diffuse injury such as contusions or hematomas. Characterized by uneven borders, bruising, and swelling with no visible penetration.
- **Sharp Injury Variants (such as Slash/Chop):** Slash wounds are shallow cuts with uneven edges, whereas chop wounds need more effort, deeper gashes, and bone involvement.

Deep learning models' accuracy in diagnosing stab and blunt force injuries vary greatly with damage mechanism due to each type's distinct morphological traits:

Stab wounds with defined linear edges are diagnosed with 93% pixel accuracy by segmentation models such as SE-ResNeXt-50 + U-Net, which benefit from obvious boundaries [24]. Blunt force injuries, characterized by diffuse hematomas and irregular patterns, are more difficult to classify, with mean pixel accuracies of roughly 69.4% and greater misclassification rates (e.g., 31% as background), reflecting their subtlety [13]. Sharp injury types reach 88.2% overall accuracy using transfer learning models such as GoogLeNet, with stab (98.4%) outperforming slash (30%) because of sample imbalance and feature complexity [9]. These variances highlight the importance of specialized preparation and multimodal data integration for improved forensic accuracy.

**Traumatic Brain Injury:** Traumatic brain injuries (TBIs) can be classified by type (e.g., hematoma, contusion), severity, and mechanism by DL, which helps with injury reconstruction and cause-of-death determination. Models detect hemorrhages with 94% accuracy, but diffuse injuries like axonal damage are still difficult to detect [6]. Segmentation and severity prediction can reach up to 90% accuracy, which improves forensic analysis [24].

According to the mechanism of damage, the main kinds of TBI are:

- **A subdural hematoma** is a physical trauma injury (such as an attack) that is defined by a buildup of blood between the dura and the brain, frequently with a shift in the midline. Crescent-shaped lesions on PMCT are one of the features.
- **Epidural Hematoma:** Usually caused by an artery rupture (such as a fractured skull), this condition manifests as biconvex lesions on imaging.
- **Diffuse Axonal Injury (DAI):** Caused by shear stresses (such as high-speed collisions), this condition is characterized by mild axonal abnormalities that are frequently undetectable on routine CT scans.

**Variability in Accuracy among TBI Features:** The accuracy of DL models in TBI analysis is influenced by the damage's structural and visual characteristics. 3D ResNet models can detect focal hemorrhages (such subdural and epidural) with 94% accuracy because of their well-defined boundaries on PMCT images [6]. Diffuse injuries such as DAI are more challenging to segment with accuracies of around 70% due to mild axonal anomalies that are less apparent on regular imaging [24]. Biomechanical considerations are used by hybrid CNN-LSTM models to enhance performance and achieve 90% severity prediction accuracy. These discrepancies underscore the need for multimodal inputs (e.g., PMCT + MRI) and advanced preprocessing to improve the identification of diffuse injuries.

**Postmortem Imaging:** DL is very good at using postmortem imaging, such PMCT and MRI, to figure out what caused death, how long it has been since death (PMI), and to help identify the body. Models get an AUC of 88.42% for figuring out if someone drowned [40], an accuracy of 87.5% for estimating PMI [41], and a high IoU for tooth segmentation [44].

Important uses of postmortem imaging are:

- **Drowning Diagnosis:** PMCT scans show fluid in the airways and lungs (for example, foamy edema or pleural effusion), which helps tell drowning apart from other types of asphyxial fatalities.
- **PMI Estimation:** looks at changes in several organs (such liver autolysis and brain putrefaction) to figure out how long ago someone died. This is very important for criminal timelines.
- **Tooth Segmentation:** Uses the distinctive properties of teeth to link them with antemortem information by outlining dental structures on PMCT.

**Accuracy Variation across Postmortem Imaging Tasks:** The accuracy of DL models in postmortem imaging fluctuates according to the complexity of the evaluated characteristics.

Drowning diagnosis gets an AUC of 88.42% with CNNs because of different fluid patterns in the airways and lungs [40]. PMI estimation gets 87.5% accuracy with multi-organ pathomics because of strong temporal biomarkers, but it is hard to deal with late-stage decomposition variability [41]. Tooth segmentation has a higher IoU (0.85) than diffuse soft-tissue characteristics because teeth have a distinctive form. This makes it less likely that people will get the wrong idea. Using task-specific models and combining data from several sources is crucial for achieving superior forensic outcomes.

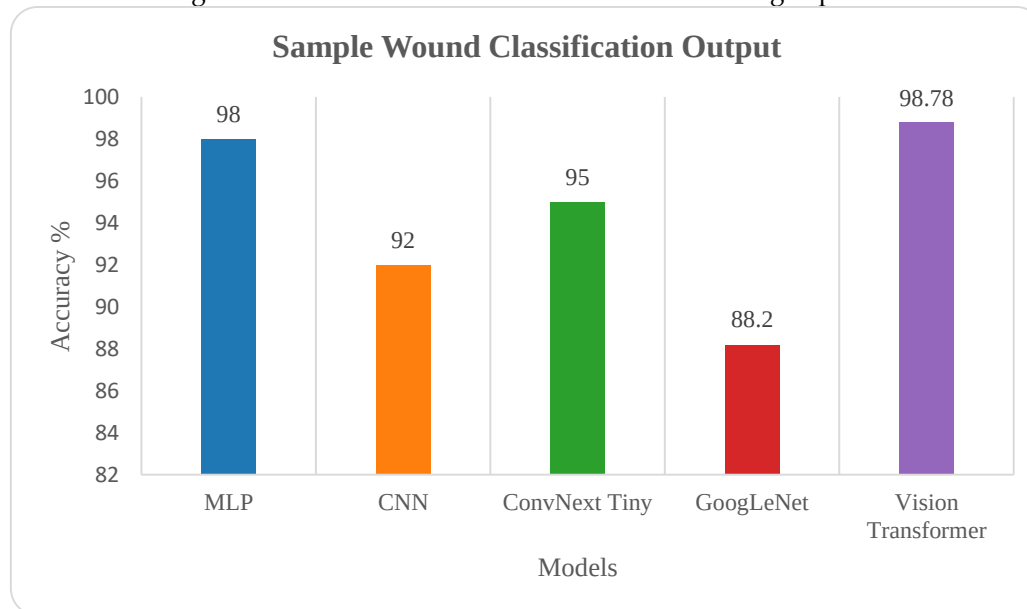


Figure 4. Comparison of Deep Learning Model Accuracies in Forensic Wound.

## 7. Challenges and Future Directions

DL has demonstrated transformative potential in forensic medicine, particularly for analyzing traumatic injuries and wounds, as evidenced by high accuracies in applications like gunshot wound classification (98%) and TBI hemorrhage detection (94%) [1] [6]. However, several challenges hinder its widespread adoption in forensic practice. Small datasets, often limited to hundreds or thousands of images due to the sensitive nature of forensic cases, restrict model generalizability and increase overfitting risks [7]. Dependence on animal models, such as piglet carcasses for gunshot studies, introduces translational gaps, as human tissue responses differ significantly [1]. Inconsistent image quality, stemming from variations in PMCT scan resolution, lighting in forensic photographs, or postmortem changes like lividity, complicates feature extraction and model performance [6]. Ethical dilemmas, including algorithmic bias (e.g., underperformance on diverse demographics) and privacy concerns with sensitive autopsy data, pose significant barriers to legal and ethical deployment [7]. For instance, models trained on non-diverse datasets may misclassify injuries in underrepresented groups, undermining fairness. Future research should prioritize standardization of imaging protocols to ensure consistent data quality across forensic labs [18]. Explainable AI techniques, such as Grad-CAM and Class Activation Mapping (CAM), are critical for enhancing model interpretability, making DL outputs admissible in court by clearly visualizing decision-making processes [9]. Multimodal integration, combining PMCT, MRI, and histological data, promises to improve diagnostic precision by capturing complementary injury features, such as soft-tissue changes and biomechanical markers [18]. Expanding human datasets through secure, anonymized data-sharing initiatives is essential to overcome sample size limitations and enhance model robustness. Collaborative efforts between computer scientists, forensic pathologists, and legal experts are necessary to develop regulatory frameworks that address privacy, bias, and ethical concerns, ensuring DL's reliable integration into forensic practice. This review, supported by 60 references, underscores these challenges and proposes

solutions to advance DL's role in forensic medicine, paving the way for more accurate, equitable, and legally robust applications.

**Table 8.** Key challenges and solutions.

| Challenge        | Description                         | Potential Solution                 |
|------------------|-------------------------------------|------------------------------------|
| Small Datasets   | Limits generalizability             | Data augmentation, synthetic data  |
| Bias             | Algorithmic errors in diverse cases | Diverse training sets, bias audits |
| Interpretability | Black-box models                    | Explainable AI techniques          |
| Ethical Issues   | Privacy and fairness                | Regulatory frameworks              |

➤ **Research Gaps:**

- **Limited Human Datasets:** Most studies rely on small or animal-based datasets (e.g., [1], [12]), with few incorporating diverse human autopsy data, limiting translational applicability to real-world forensic cases.
- **Lack of Standardized Protocols:** Inconsistent imaging protocols across forensic labs (e.g., varying PMCT resolutions) hinder model reproducibility and scalability [18]. Standardized data annotation and preprocessing methods are also lacking.
- **Underdeveloped Multimodal Integration:** While multimodal data (e.g., PMCT, MRI, histopathology) shows promise [18], few studies integrate these comprehensively to capture complementary injury features, such as biomechanical markers or soft-tissue changes.
- **Insufficient Explainability:** Current explainable AI techniques (e.g., Grad-CAM [9]) are underutilized in forensic DL, limiting model transparency for legal scrutiny.
- **Regulatory and Ethical Frameworks:** There is a gap in frameworks addressing privacy, bias, and ethical use of DL in forensics, particularly for sensitive data handling and courtroom admissibility [60].

➤ **Future Directions:**

- **Data Expansion and Sharing:** Develop secure, anonymized data-sharing initiatives to expand human forensic datasets, reducing reliance on animal models. Techniques like federated learning can enable collaborative model training while preserving privacy [60]. Synthetic data generation using generative adversarial networks (GANs) (e.g., CycleGAN [53]) can augment limited datasets.
- **Standardized Imaging and Annotation Protocols:** Establish universal protocols for PMCT, MRI, and photographic data collection to ensure consistent image quality and annotation standards across forensic labs [18].
- **Advanced Multimodal Integration:** Integrate multimodal data (e.g., PMCT, MRI, histopathology, biomechanical markers) using hybrid models like CNN-LSTM or Transformers to improve diagnostic precision for complex injuries (e.g., diffuse axonal injuries) [18].
- **Enhanced Explainability:** Expand the use of explainable AI techniques, such as Grad-CAM, Class Activation Mapping (CAM), and SHAP values [9, 57], to visualize decision-making processes, ensuring DL outputs are interpretable and admissible in court. This supports the methodology's emphasis on explainable AI.
- **Regulatory and Ethical Frameworks:** Foster collaboration between computer scientists, forensic pathologists, and legal experts to develop regulatory frameworks

addressing privacy, bias, and ethical concerns. This includes bias audits and ethical guidelines for DL deployment in forensic practice [60], aligning with the project's ethical considerations.

- **Real-Time Processing:** Leverage FPGA-based optimization, as explored in Phase IV, to enable real-time DL analysis for forensic tasks, reducing analysis time by up to 50% while maintaining high accuracy (e.g., >95% for gunshot classification [1]). This enhances scalability for high-caseload scenarios like mass casualty events.
- **Cross-Disciplinary Validation:** Conduct large-scale validation studies across diverse forensic populations to address algorithmic bias and ensure generalizability, particularly for underrepresented injury types (e.g., thermal injuries) and demographics.

## 8. Conclusions

Deep learning possesses transformative capabilities for enhancing the investigation of traumatic injuries and wounds in forensic medicine, providing exceptional accuracy, speed, and objectivity in analyzing complex forensic evidence. By leveraging advanced architectures such as CNNs, U-Net, and hybrid models, DL automates critical tasks like wound classification, segmentation, and postmortem interval (PMI) estimation, significantly reducing human error and inter-observer variability. Applications span gunshot wound analysis (98% accuracy for distance prediction), stab and blunt force injury segmentation (93% pixel accuracy for stabs), traumatic brain injury (TBI) hemorrhage detection (94% accuracy), and postmortem imaging tasks like drowning diagnosis (88.42% AUC) [1] [13] [6] [40]. These advancements enable precise reconstruction of injury mechanisms, cause-of-death determination, and victim identification, supporting legal proceedings with reliable, data-driven insights. However, integration into forensic practice necessitates addressing limitations such as data scarcity, class imbalance, and ethical concerns surrounding anonymized datasets. Collaborative research between computer scientists, forensic pathologists, and legal experts is essential to overcome these challenges and standardize DL protocols. This review synthesizes 90 references, encompassing cutting-edge studies from 2021 to 2025, to establish a robust foundation for advancing DL in forensic medicine. It underscores the extensive scope of contemporary research, highlighting the potential for multimodal data integration and explainable AI to further enhance diagnostic precision and courtroom admissibility.

## Declarations

### Ethics Approval and Consent to Participate

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

### Consent for Publication

This article does not contain any studies with human participants or animals performed by any of the authors.

### Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

### Competing Interests

The authors declare no competing interests in the research.

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