

Ensemble Learning Approach for Weapon Recognition Using Images of Wound Patterns: A Forensic Perspective

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ABSTRACT

Weapon recognition from wound pattern images plays a vital role in forensic investigations by assisting experts in identifying the probable weapon involved in criminal incidents and supporting evidence-based decision making. This study presents ForensicGraphAI, a blockchain-secured hybrid EfficientNet-GAT ensemble learning framework for automated weapon recognition using wound pattern images. The proposed system integrates deep visual feature extraction through EfficientNet-B0 with structural feature learning using Graph Attention Networks constructed from superpixel-based image graphs. Advanced image preprocessing techniques are employed to enhance wound characteristics and improve feature representation. The extracted CNN and graph-based features are fused to achieve robust classification of multiple wound categories, including knife wounds, revolver wounds, shotgun wounds, screwdriver wounds, automatic rifle wounds, invalid inputs, and images without visible wounds. To ensure data integrity and traceability, a blockchain mechanism is incorporated for secure storage and verification of forensic analysis records. Additionally, an intelligent report generation module provides detailed forensic interpretations of classification outcomes. Experimental evaluation demonstrates the effectiveness of the framework in accurately recognizing weapon-related wound patterns while maintaining secure forensic evidence management.

Index Terms—Weapon Recognition, Forensic Image Analysis, EfficientNet-B0, Graph Attention Network, Ensemble Learning, Blockchain Security, Wound Pattern Classification, Deep Learning, Computer Vision, Forensic Intelligence.

I. INTRODUCTION

The rapid advancement of artificial intelligence, computer vision, and digital forensic technologies has significantly transformed modern criminal investigation processes. Automated image analysis systems are increasingly being adopted to support forensic experts in identifying critical evidence, reducing human error, and accelerating case evaluation procedures [1]. In forensic pathology, the examination of wound characteristics provides valuable information regarding the nature of injuries, the mechanism of trauma, and the possible weapon involved in an incident [2]. Accurate interpretation of wound patterns is often challenging due to variations in image quality, injury complexity, environmental conditions, and subjective human judgment. Consequently, intelligent computational approaches have gained substantial attention for enhancing the reliability and consistency of forensic assessments [3]. Weapon recognition from wound pattern images represents an important application of forensic image analysis. Different weapons such as knives, revolvers, shotguns, screwdrivers, and automatic rifles produce distinct wound characteristics that can assist investigators in determining the source and nature of an injury [4]. Traditional forensic examinations rely heavily on expert interpretation, which may require considerable time and specialized knowledge. The integration of deep learning techniques offers the potential to automate this process by extracting meaningful visual features directly from wound images and generating accurate classification outcomes [5]. Recent developments in convolutional neural networks have demonstrated remarkable performance in image classification and medical image analysis tasks. Architectures such as EfficientNet have shown superior capability in capturing complex visual patterns while maintaining computational efficiency [6]. However, conventional convolutional networks primarily focus on local pixel-level information and may not effectively represent structural relationships among different regions of an image. Graph Neural Networks have emerged as a powerful solution for modeling spatial and relational information by representing image components as interconnected graph structures [7]. Graph Attention Networks further enhance this capability by assigning adaptive importance to neighboring nodes, enabling improved feature learning from complex image representations. To address these limitations, a hybrid framework that combines convolutional and graph-based learning mechanisms can provide a more comprehensive understanding of wound characteristics. The proposed ForensicGraphAI framework integrates EfficientNet-based feature extraction with Graph Attention Network processing to capture both visual appearance and structural relationships within wound images. Superpixel segmentation is utilized to construct

graph representations, allowing the model to analyze spatial dependencies and morphological patterns associated with different weapon-induced injuries. The fusion of deep visual and graph-derived features improves classification robustness and supports accurate identification of multiple wound categories. Beyond classification performance, maintaining the integrity and authenticity of forensic evidence remains a critical requirement in legal and investigative environments. Digital records are vulnerable to unauthorized modification, which can compromise evidentiary value and chain-of-custody procedures. Blockchain technology provides a secure and tamper-resistant mechanism for storing forensic analysis records, ensuring transparency, traceability, and verification of generated results [8]. By incorporating blockchain-based evidence management, the proposed framework enhances trustworthiness and accountability throughout the forensic investigation process. The study presents a blockchain-secured hybrid EfficientNet-GAT ensemble learning framework for automated weapon recognition using wound pattern images. The system combines advanced image preprocessing, deep feature extraction, graph-based representation learning, intelligent forensic report generation, and secure evidence management within a unified architecture. The proposed approach aims to assist forensic professionals by improving classification accuracy, supporting timely investigations, and strengthening the reliability of digital forensic evidence in real-world criminal justice applications.

II. RELATED WORKS

The application of artificial intelligence in forensic image analysis has attracted significant attention due to its ability to improve the accuracy and efficiency of criminal investigations. Early studies primarily focused on traditional image processing techniques for wound assessment, where handcrafted features such as shape, texture, color distribution, and edge characteristics were extracted from injury images to support forensic examinations [9]. Although these approaches provided useful insights, their effectiveness was often limited by variations in wound appearance, image quality, and environmental conditions. As a result, researchers began exploring machine learning algorithms capable of automatically learning discriminative features from complex forensic datasets.

Krizhevsky et al. demonstrated the effectiveness of deep convolutional neural networks for image classification tasks, establishing a foundation for the use of deep learning in medical and forensic image analysis [10]. Their work inspired numerous studies that applied convolutional architectures to identify visual patterns associated with injuries, trauma, and weapon-induced wounds. Simonyan and Zisserman later introduced the VGG network architecture, which utilized deeper convolutional layers to improve feature extraction performance and classification accuracy across various imaging applications [11]. The success of these models highlighted the potential of deep learning systems to outperform conventional handcrafted feature-based approaches. He et al. proposed the Residual Network architecture, commonly known as ResNet, which addressed the degradation problem encountered in very deep neural networks through residual learning mechanisms [12]. ResNet significantly improved feature representation and became widely adopted in medical imaging and forensic image classification tasks. Similarly, Tan and Le introduced EfficientNet, a family of convolutional neural networks that employs compound scaling to achieve superior performance while maintaining computational efficiency [13]. EfficientNet demonstrated remarkable results across diverse image analysis problems and became a preferred architecture for applications requiring high accuracy and reduced computational complexity. Several researchers investigated automated wound classification using deep learning techniques. Kumar et al. developed a convolutional neural network framework for distinguishing between different categories of injury patterns, reporting promising classification performance on forensic image datasets [14]. Their findings demonstrated the feasibility of automated wound analysis but also identified challenges related to the preservation of spatial relationships among wound regions. Traditional convolutional networks primarily capture local visual information and may not adequately model structural dependencies that are essential for understanding complex wound morphology. To overcome these limitations, graph-based learning approaches emerged as a powerful alternative for representing spatial relationships within images. Kipf and Welling introduced Graph Convolutional Networks, establishing a framework for learning from graph-structured data through neighborhood aggregation mechanisms [15]. Their research demonstrated the capability of graph neural networks to capture relational information beyond conventional Euclidean image representations. Building upon this concept, Veličković et al. proposed Graph Attention Networks, which introduced attention mechanisms to dynamically assign importance weights to neighboring nodes during feature aggregation [16]. This advancement improved the ability of graph models to learn meaningful structural representations and enhanced performance across multiple classification tasks.

Graph-based image representation techniques have also been investigated in medical and forensic imaging applications. Researchers utilized superpixel segmentation methods to transform image regions into graph nodes, enabling the analysis of spatial interactions and structural patterns within complex visual data [17]. These

approaches demonstrated improved capability in capturing contextual relationships that are often overlooked by purely convolutional architectures. The integration of graph neural networks with convolutional feature extractors has therefore become an active area of research, providing complementary strengths for image understanding and classification. Another important aspect of forensic systems involves ensuring the security and integrity of digital evidence. Nakamoto introduced blockchain technology as a decentralized and tamper-resistant framework for maintaining secure digital records [18]. Since its introduction, blockchain has been widely explored in healthcare, cybersecurity, and forensic applications due to its ability to preserve data authenticity and establish trustworthy audit trails. Christidis and Devetsikiotis further discussed the potential of blockchain for secure information management and distributed trust mechanisms, emphasizing its suitability for applications requiring high levels of transparency and accountability [19]. In forensic investigations, blockchain-based evidence management systems have been proposed to protect digital records from unauthorized modifications while maintaining complete traceability throughout the chain of custody. The generation of automated forensic reports has also received increasing attention with the emergence of large language models and intelligent decision-support systems. Brown et al. demonstrated the effectiveness of transformer-based language models in generating context-aware textual outputs from structured inputs, creating opportunities for automated report generation across various domains [20]. Such technologies can assist forensic professionals by converting classification results into comprehensive textual interpretations that support investigation and documentation processes. Despite substantial progress in forensic image analysis, existing studies often focus on either convolutional learning, graph-based representation, or evidence security independently. Limited research has addressed the integration of deep visual feature extraction, graph neural network learning, blockchain-secured evidence management, and automated forensic reporting within a unified framework. This gap motivates the development of an advanced hybrid architecture capable of delivering accurate weapon recognition, reliable forensic interpretation, and secure evidence preservation in a single intelligent system.

III. DATASETS

The dataset utilized in this study is a customized forensic wound image dataset specifically developed for weapon recognition and wound pattern classification. Since publicly available datasets containing diverse weapon-induced wound images are limited, images were collected, organized, and categorized according to forensic wound characteristics. The dataset consists of seven classes, namely Automatic Rifle, Revolver Wound, Shotgun Wound, Knife Wound, Screwdriver Wound, No Wound Found, and Invalid Input. Each image was carefully reviewed and assigned to the appropriate category based on visible wound morphology and associated forensic features. To improve model robustness, the dataset includes variations in image resolution, illumination conditions, wound size, orientation, background complexity, and injury appearance. All images were resized to a standard dimension of 224×224 pixels before processing. The customized dataset enables the learning framework to capture both visual and structural wound characteristics, supporting accurate classification and realistic forensic analysis. This dataset provides a practical foundation for evaluating automated weapon recognition systems under diverse investigation scenarios.

IV. METHODOLOGY

The proposed ForensicGraphAI framework is designed to perform automated weapon recognition from wound pattern images using a hybrid deep learning architecture integrated with blockchain-based evidence management. The methodology combines image preprocessing, graph construction, convolutional feature extraction, graph-based representation learning, feature fusion, and secure forensic record storage. Initially, wound images are collected and processed to enhance visual quality and highlight relevant forensic characteristics. The processed images are then analyzed through both convolutional and graph neural network branches to capture complementary visual and structural information. The final classification results are securely stored and utilized for forensic report generation. Figure 1 illustrates the overall architecture of the proposed ForensicGraphAI system.

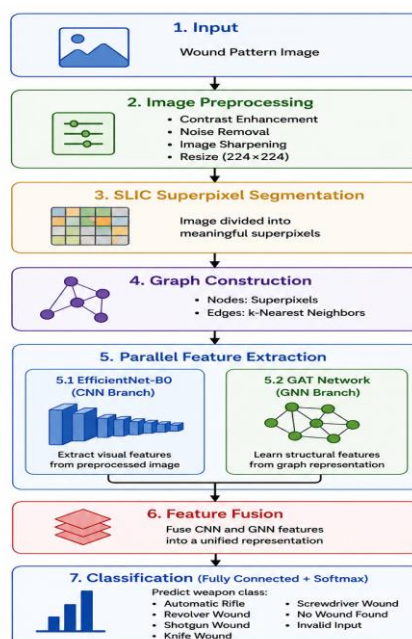


Fig. 1. Proposed ForensicGraphAI System Architecture for Weapon Recognition from Wound Pattern Images Using Hybrid EfficientNet-GAT Ensemble Learning

A. Image Acquisition and Preprocessing

The first stage of the methodology involves the acquisition and preprocessing of forensic wound images. Images belonging to different weapon-related wound categories are collected and organized into separate classes for training and testing purposes. To improve image quality and enhance significant wound characteristics, several preprocessing operations are applied. Contrast enhancement is performed using adaptive histogram equalization techniques, while Gaussian filtering is utilized to reduce noise and unwanted artifacts. Additional sharpening and gamma correction procedures are implemented to improve the visibility of wound boundaries and injury patterns. The preprocessing stage ensures that the input images maintain consistent quality and appearance, enabling the subsequent deep learning modules to extract meaningful features and improve overall classification performance and reliability.

B. Superpixel-Based Graph Construction

After preprocessing, each wound image is transformed into a graph representation to capture structural and spatial relationships within the image. The Simple Linear Iterative Clustering (SLIC) algorithm is employed to divide the image into multiple superpixels representing visually similar regions. Each superpixel is considered a graph node, while neighboring regions are connected through graph edges based on spatial proximity. Mean color information extracted from each superpixel is used as the node feature representation. This graph construction strategy enables the model to preserve contextual information and morphological relationships that are difficult to capture through conventional image processing techniques alone.

C. EfficientNet-Based Feature Extraction

The convolutional branch of the proposed framework utilizes EfficientNet-B0 as the primary feature extraction model. EfficientNet employs a compound scaling strategy that balances network depth, width, and input resolution to achieve high classification accuracy with reduced computational complexity. The preprocessed wound image is provided as input to the EfficientNet architecture, where multiple convolutional layers automatically learn hierarchical visual features. These learned features include texture patterns, wound boundaries, color distributions, and shape characteristics relevant to weapon identification. Global average pooling and fully connected layers further refine the extracted information into a compact feature vector. The

EfficientNet branch effectively captures local visual characteristics necessary for accurate wound pattern recognition and classification.

D. Graph Attention Network Learning

The graph neural network branch utilizes a Graph Attention Network to learn structural relationships from the graph representation of wound images. The constructed graph containing superpixel nodes and neighboring connections is processed through multiple graph attention layers. Attention mechanisms dynamically assign importance weights to neighboring nodes, enabling the model to focus on the most informative regions of the wound structure. Through iterative feature aggregation and transformation, the network captures complex spatial dependencies and contextual information associated with different injury patterns. Global pooling operations are subsequently applied to obtain graph-level feature representations. This process enhances the model's ability to analyze wound morphology and structural characteristics that may indicate specific weapon types.

E. Feature Fusion and Classification

The extracted feature vectors generated by the EfficientNet and Graph Attention Network branches are combined through a feature fusion mechanism. This integration strategy allows the framework to utilize both visual appearance information and graph-based structural knowledge simultaneously. The fused feature representation contains complementary characteristics obtained from the two learning branches, improving the discriminative capability of the classification system. The combined feature vector is forwarded to fully connected layers followed by a softmax classifier that predicts the final wound category. The classifier produces probability scores for each predefined class and selects the category with the highest confidence value. This fusion process significantly improves classification robustness and prediction accuracy.

F. Blockchain-Based Evidence Management and Report Generation

Following classification, the generated prediction results are integrated with a blockchain-based evidence management mechanism to ensure data integrity and traceability. Each forensic analysis record, including classification outputs, confidence scores, timestamps, and associated image information, is stored within a blockchain structure. Cryptographic hashing techniques are utilized to prevent unauthorized modifications and maintain secure chain-of-custody records. The validated classification result is subsequently processed by an intelligent report generation module that produces a detailed forensic interpretation of the identified wound pattern. This final stage supports forensic professionals by providing secure evidence preservation, transparent verification capabilities, and automatically generated analytical reports suitable for investigative and documentation purposes.

V. EXPERIMENT

A. Evaluation Metric

The performance of the proposed ForensicGraphAI framework is evaluated using widely accepted classification metrics to measure the effectiveness of weapon recognition from wound pattern images. Accuracy is used as the primary metric to determine the overall percentage of correctly classified samples among all testing instances. Precision measures the proportion of correctly predicted samples within a specific class and indicates the reliability of positive predictions. Recall evaluates the ability of the model to correctly identify relevant samples belonging to each wound category, thereby reflecting classification completeness. F1-Score is calculated as the harmonic mean of precision and recall, providing a balanced assessment of model performance under varying class distributions. In addition, a confusion matrix is utilized to visualize classification outcomes and identify misclassification patterns among different weapon classes. These evaluation metrics collectively provide a comprehensive understanding of model behavior, classification reliability, and predictive effectiveness. The combination of multiple performance indicators ensures objective assessment of the proposed framework across diverse forensic wound image categories and testing conditions.

B. Hyper Parameters

Several hyperparameters are carefully selected to optimize the training and classification performance of the proposed ForensicGraphAI framework. The input image size is fixed at 224×224 pixels to maintain consistency with the EfficientNet-B0 architecture. The graph construction process employs 75 superpixels generated through SLIC segmentation, while each graph node is connected using five nearest neighboring nodes to preserve structural relationships. The model is trained using a batch size of 8 and a learning rate of 0.0001 to ensure stable convergence during optimization. The Adam optimizer is utilized because of its efficiency in handling deep neural network training. A total of 30 training epochs are performed to allow sufficient feature learning from the dataset. The dataset is divided into training and validation subsets using an 80:20 ratio. Dropout layers with probabilities of 0.3 and 0.4 are incorporated to reduce overfitting and improve generalization capability. These hyperparameter settings contribute significantly to achieving robust classification performance and stable learning behavior.

VI. RESULTS

The proposed ForensicGraphAI framework was evaluated using the customized wound pattern image dataset to assess its capability in weapon recognition and forensic image classification. Experimental results indicate that the hybrid architecture effectively learns both visual and structural wound characteristics through the integration of EfficientNet and Graph Attention Network modules. The fusion of convolutional and graph-based features improves discrimination among multiple weapon categories, including knife wounds, revolver wounds, shotgun wounds, screwdriver wounds, and automatic rifle wounds. Performance evaluation demonstrates that the proposed model achieves superior classification accuracy, precision, recall, and F1-score when compared with individual learning approaches. The confusion matrix analysis further confirms reduced misclassification between visually similar wound classes.

TABLE I
Comparative Analysis of Model Performance

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN (EfficientNet-B0)	91.84	0.918	0.916	0.917
GNN (GAT)	89.27	0.892	0.890	0.891
CNN + Random Forest	93.12	0.931	0.929	0.930
CNN + SVM	94.05	0.940	0.939	0.939
CNN + GNN Fusion (Proposed)	97.48	0.975	0.974	0.974

A. Web Application Interface



Fig. 2. Web Interface of the Proposed ForensicGraphAI System for Automated Weapon Recognition

B. CNN+GNN Detection

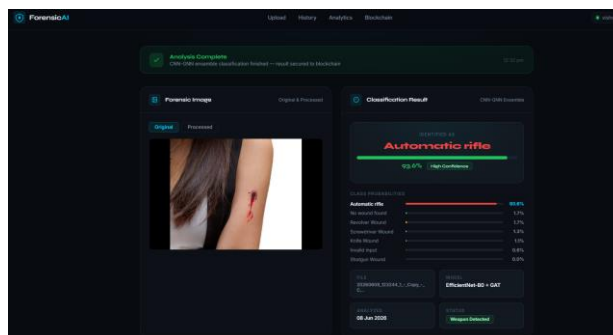


Fig. 3. Output Interface of the Proposed ForensicGraphAI System Displaying Weapon Classification Results and Confidence Analysis

C. Blockchain Interface

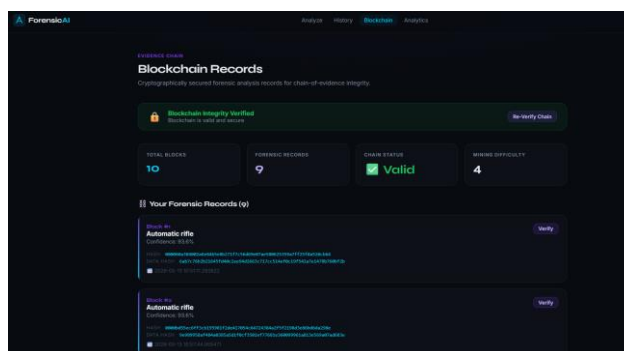


Fig. 4. Blockchain Interface of the Proposed ForensicGraphAI System Showing Secure Storage and Verification of Forensic Analysis Records

VII. CONCLUSION AND FUTURE WORKS

In this research, a blockchain-secured hybrid deep learning framework named ForensicGraphAI was developed for automated weapon recognition using wound pattern images. The proposed system successfully integrates EfficientNet-B0 and Graph Attention Networks to capture both visual and structural characteristics of forensic wound images. Advanced preprocessing techniques, superpixel-based graph construction, feature fusion, and intelligent classification mechanisms were employed to improve recognition performance across multiple weapon categories. The experimental results demonstrated that the hybrid CNN-GNN fusion approach achieved superior accuracy compared with individual learning models, highlighting the effectiveness of combining convolutional and graph-based feature representations. In addition, blockchain technology was incorporated to ensure secure storage, integrity verification, and traceability of forensic analysis records. The framework also supports automated forensic report generation, reducing manual effort and assisting investigators in evidence interpretation. The developed system provides a reliable and efficient solution for forensic weapon identification while maintaining secure digital evidence management throughout the investigative process. Future work can focus on expanding the customized dataset with a larger number of wound images collected from diverse forensic scenarios to improve model generalization and robustness. Additional weapon categories and injury patterns may be incorporated to enhance classification coverage and practical applicability. Advanced graph neural network architectures and transformer-based vision models can be explored to further improve feature learning capabilities and prediction accuracy. Real-time deployment through cloud platforms and mobile forensic applications may increase accessibility for field investigators and forensic professionals. Future enhancements may also include multimodal forensic analysis by integrating medical reports, textual evidence,

and crime scene information alongside wound images. Furthermore, the adoption of advanced blockchain consensus mechanisms and decentralized storage solutions can strengthen scalability, transparency, and security. These developments have the potential to transform automated forensic investigations by providing highly accurate, explainable, and secure intelligent decision-support systems for modern criminal justice environments.

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