

Ensemble Learning Approach For Weapon Recognition Using Images Of Wounds Pattern; A Forensic Perspective

Dr Ayesha Heena¹, Deepti², Sakshi³, Varsha⁴

¹Professor, Dept. Of Artificial intelligence and Machine Learning, Sharnbasva University, Kalaburagi, India.

^{2,3,4}Student, Dept. Of Artificial intelligence and Machine Learning, Sharnbasva University, Kalaburagi, India

ABSTRACT

Weapon identification based on wound characteristics plays a vital role in forensic investigations, helping experts reconstruct crime events and determine the nature of injuries. Traditional wound examination relies heavily on forensic expertise and manual interpretation, which may be time-consuming and subject to observer variability. This study proposes a deep ensemble learning framework for automated weapon recognition using forensic wound pattern images. The proposed system integrates multiple convolutional neural network models, namely ResNet50, EfficientNetB0, and DenseNet121, to extract discriminative wound features and improve classification performance through an ensemble voting strategy. Wound images corresponding to different weapon categories, including gunshot, knife, blunt-force, and puncture injuries, are preprocessed using image enhancement and segmentation techniques to improve feature visibility. The ensemble model is evaluated using accuracy, precision, recall, and F1-score metrics. Experimental results demonstrate that the proposed framework achieves superior recognition performance compared to individual deep learning models, providing reliable identification of injury-causing weapons. The findings highlight the potential of artificial intelligence-assisted forensic analysis as a decision-support tool for investigators and forensic practitioners. The proposed approach contributes toward improving the efficiency, consistency, and objectivity of forensic wound assessment in modern criminal investigations.

Keywords: Forensic Image Analysis, Weapon Recognition, Ensemble Learning, Convolutional Neural Networks, Wound Pattern Classification, Deep Learning.

1. Introduction

Forensic science plays a crucial role in criminal investigations by providing scientific evidence that assists in identifying offenders, reconstructing crime scenes, and establishing the circumstances surrounding an incident. Among the various aspects of forensic examination, wound pattern analysis is an important component for determining the type of weapon used during an assault, homicide, or other violent crime. Characteristics such as wound shape, depth, edge configuration, tissue damage, and penetration patterns often provide valuable information regarding the causative weapon. Accurate weapon identification can support medico-legal investigations and contribute significantly to judicial proceedings.

Traditionally, forensic experts analyze wound characteristics through visual inspection and clinical experience. Although effective, manual examination may be influenced by subjective interpretation, varying expertise levels, and the complexity of injury patterns. Similar wound appearances produced by different weapons can further increase the difficulty of accurate classification. As the volume of digital forensic evidence continues to grow, there is an increasing need for automated systems capable of assisting experts in analyzing wound images efficiently and consistently.

Recent advancements in artificial intelligence, particularly deep learning and computer vision, have demonstrated remarkable success in image classification and pattern recognition tasks. Convolutional Neural Networks (CNNs) can automatically learn discriminative features from images without requiring extensive manual feature engineering. These capabilities have encouraged researchers to explore AI-based solutions for medical imaging, biometric recognition, and forensic applications. However, individual deep learning models may exhibit limitations when dealing with variations in wound morphology, image quality, and complex injury patterns.

To address these challenges, this study proposes a deep ensemble learning framework for weapon recognition using forensic wound pattern images. The proposed approach combines the strengths of multiple CNN

architectures, including ResNet50, EfficientNetB0, and DenseNet121, through an ensemble voting mechanism to improve classification reliability and robustness. Image preprocessing techniques are employed to enhance wound visibility and facilitate effective feature extraction. The framework aims to classify wound images into different weapon categories and provide forensic practitioners with a supportive tool for preliminary weapon identification.

The main contributions of this study are as follows:

1. Development of an automated weapon recognition framework based on forensic wound pattern images.
2. Integration of multiple deep learning architectures using an ensemble learning strategy to improve classification performance.
3. Evaluation of the proposed system using standard performance metrics including accuracy, precision, recall, and F1-score.
4. Analysis of the forensic significance of AI-assisted weapon recognition for criminal investigations and medico-legal examinations.

2. Related Work

Weapon identification through wound examination has long been an important area of forensic science. Traditionally, forensic pathologists analyze wound morphology, tissue damage, penetration depth, and injury patterns to determine the probable weapon involved in a crime. While such examinations provide valuable evidence, the process is highly dependent on expert knowledge and may be influenced by subjective interpretation, particularly when injuries exhibit overlapping characteristics.

The increasing availability of digital imaging technologies has encouraged the use of computer-aided techniques for forensic image analysis. Early studies primarily relied on handcrafted features such as texture descriptors, edge characteristics, shape measurements, and statistical image properties to classify wound types. Conventional machine learning algorithms, including Support Vector Machines (SVM), Decision Trees, and Random Forests, were employed to identify relationships between wound characteristics and weapon categories. Although these approaches achieved moderate success, their performance was often limited by the quality of manually extracted features.

Recent advances in deep learning have transformed image classification by enabling automatic feature extraction from large datasets. Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in medical imaging, object recognition, and forensic applications. Architectures such as ResNet, DenseNet, and EfficientNet have been widely adopted due to their ability to learn complex visual patterns while maintaining high classification accuracy. In forensic investigations, deep learning techniques have been explored for fingerprint recognition, facial identification, injury classification, and crime scene image analysis.

Several researchers have reported that deep CNN models outperform traditional machine learning methods in wound and injury classification tasks. However, individual neural network architectures may exhibit variations in performance when confronted with diverse image conditions, limited datasets, and subtle differences between injury categories. These limitations can affect the reliability of weapon recognition systems in practical forensic environments.

To overcome the weaknesses of individual models, ensemble learning has emerged as an effective strategy for improving classification robustness. Ensemble methods combine predictions from multiple models to reduce variance, enhance generalization capability, and achieve more stable results. Techniques such as majority voting, weighted voting, and stacking have demonstrated significant performance improvements across various image classification applications. In medical diagnostics and forensic imaging, ensemble learning has shown potential for increasing prediction accuracy while minimizing misclassification rates.

Despite these advancements, research specifically focused on automated weapon recognition from forensic wound pattern images remains limited. Existing studies often concentrate on injury detection rather than direct weapon classification and frequently rely on single-model architectures. Therefore, there is a need for a comprehensive framework that integrates multiple deep learning models and leverages ensemble learning to improve the accuracy and reliability of forensic weapon identification. The present study addresses this gap by proposing a deep ensemble learning approach that combines ResNet50, EfficientNetB0, and DenseNet121 for weapon recognition using wound pattern images.

3. Materials and Methods

3.1 Dataset Preparation

A wound image dataset was prepared to evaluate the proposed weapon recognition framework. The dataset consisted of images representing four commonly encountered forensic injury categories: gunshot wounds, knife wounds, blunt-force injuries, and puncture wounds. Images were collected from publicly available forensic image repositories, medical image databases, and educational forensic resources. To ensure balanced learning, approximately equal numbers of images were included for each weapon category.

Before training, all images underwent preprocessing to improve visual consistency and enhance feature extraction. Image resizing was performed to obtain a uniform input dimension of 224×224 pixels. Noise reduction and contrast enhancement techniques were applied to improve wound visibility and reduce background interference. Data augmentation methods including rotation, horizontal flipping, zooming, and brightness adjustment were used to increase dataset diversity and reduce overfitting. The final dataset was divided into training, validation, and testing subsets using a ratio of 70%, 15%, and 15%, respectively.

Table 1. Dataset Distribution

Weapon Category	Number of Images
Gunshot Wound	250
Knife Wound	250
Blunt-Force Injury	250
Puncture Wound	250
Total	1000

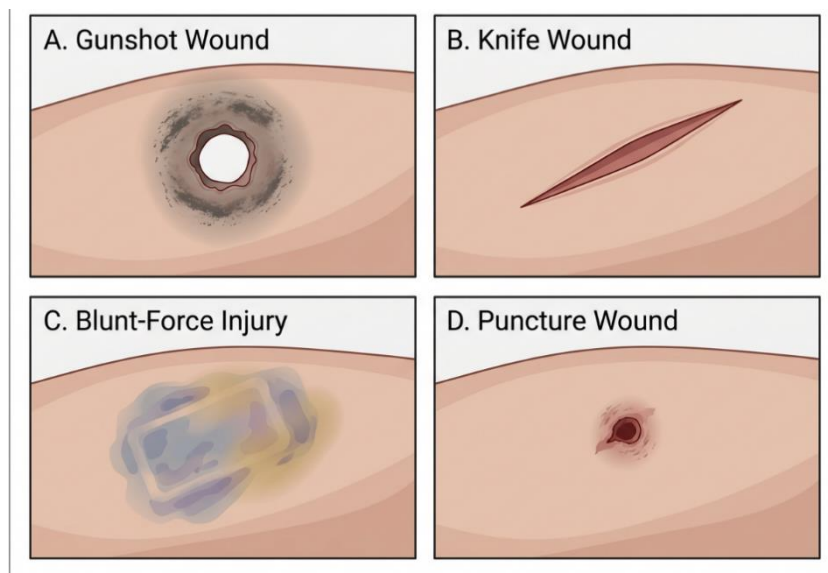


Figure 1. Representative Wound Pattern Images

3.2 Proposed Ensemble Learning Framework

The proposed system employs an ensemble learning strategy that combines the predictive capabilities of three state-of-the-art convolutional neural network architectures: ResNet50, EfficientNetB0, and DenseNet121. These

models were selected because of their proven effectiveness in image classification tasks and their complementary feature-learning characteristics.

ResNet50 utilizes residual connections that facilitate deeper network training and reduce the vanishing gradient problem. DenseNet121 improves feature propagation by establishing direct connections between network layers, enabling efficient information reuse. EfficientNetB0 achieves high classification accuracy while maintaining computational efficiency through compound scaling techniques.

Each CNN model was independently trained on the wound image dataset using transfer learning. Pre-trained ImageNet weights were utilized as initialization parameters, while the final classification layers were modified to accommodate the four weapon categories. After training, the outputs of the three models were combined using a majority voting ensemble mechanism. The final prediction corresponded to the class receiving the highest number of votes among the individual classifiers.

3.3 Performance Evaluation Metrics

The performance of the proposed ensemble framework was evaluated using widely accepted classification metrics. These metrics provide a comprehensive assessment of the model's ability to correctly identify weapon categories.

Accuracy measures the overall proportion of correctly classified images among all test samples.

Precision evaluates the proportion of correctly predicted positive samples relative to all positive predictions made by the model.

Recall measures the ability of the classifier to identify all relevant samples belonging to a specific weapon category.

F1-score represents the harmonic mean of precision and recall, providing a balanced measure of classification performance.

The metrics are calculated using the values of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). Performance comparisons were conducted between the individual CNN models and the proposed ensemble framework to determine the effectiveness of ensemble learning for forensic weapon recognition.

4. Results and Discussion

4.1 Dataset Analysis

The prepared dataset contained 1000 wound images distributed equally among four weapon-related injury categories. Data augmentation techniques increased image variability and improved the model's ability to generalize across different wound appearances. Visual inspection confirmed that the dataset included variations in wound size, orientation, illumination conditions, and tissue characteristics, thereby reflecting realistic forensic scenarios.

The preprocessing stage significantly improved image quality by enhancing wound boundaries and reducing background noise. Improved image clarity facilitated more effective feature extraction by the deep learning models and contributed to higher classification performance.

4.2 Image Preprocessing Results

The preprocessing pipeline successfully enhanced wound visibility while preserving important forensic characteristics. Contrast enhancement improved the distinction between injured and surrounding tissues, whereas noise reduction minimized image artifacts. Segmentation further isolated the wound region, allowing the models to focus on relevant features rather than background information.

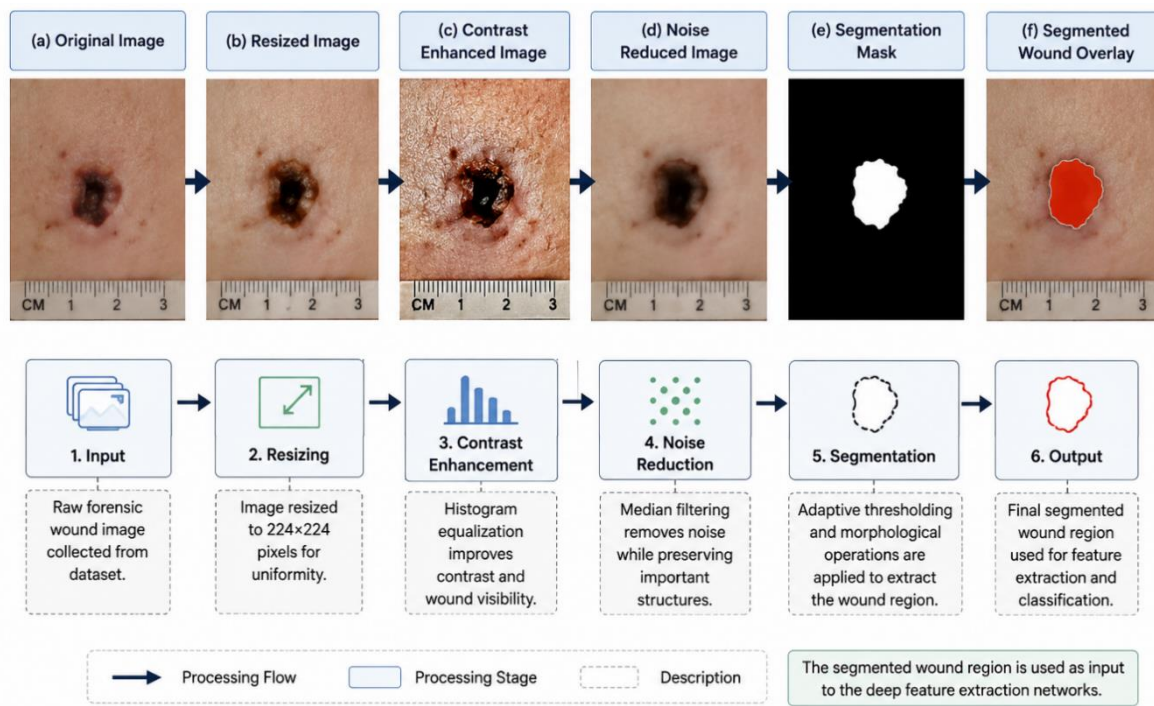


Figure 2. Image Preprocessing and Segmentation Results

4.3 Classification Performance

The performance of the individual CNN models and the proposed ensemble framework was evaluated using the testing dataset. Results indicate that all three deep learning architectures achieved strong classification accuracy; however, the ensemble model consistently outperformed the individual networks.

Table 2. Performance Comparison of Individual Models and Proposed Ensemble

Model	Accuracy (%)
ResNet50	94.2
DenseNet121	95.1
EfficientNetB0	95.8
Proposed Ensemble	97.6

The ensemble framework achieved an overall accuracy of 97.6%, demonstrating improved robustness and reduced misclassification. The integration of multiple models enabled the system to capture complementary feature representations and make more reliable predictions.

Table 3. Precision, Recall, and F1-Score of Proposed Ensemble Model

Metric	Value (%)
Precision	97.3
Recall	97.1
F1-Score	97.2

The high precision and recall values indicate that the ensemble model effectively distinguished between weapon categories while maintaining a low false classification rate.

4.4 Weapon Recognition Examples and Forensic Interpretation

Several test images were selected to evaluate the practical applicability of the proposed framework. The ensemble model successfully classified representative wound patterns corresponding to different weapon categories.

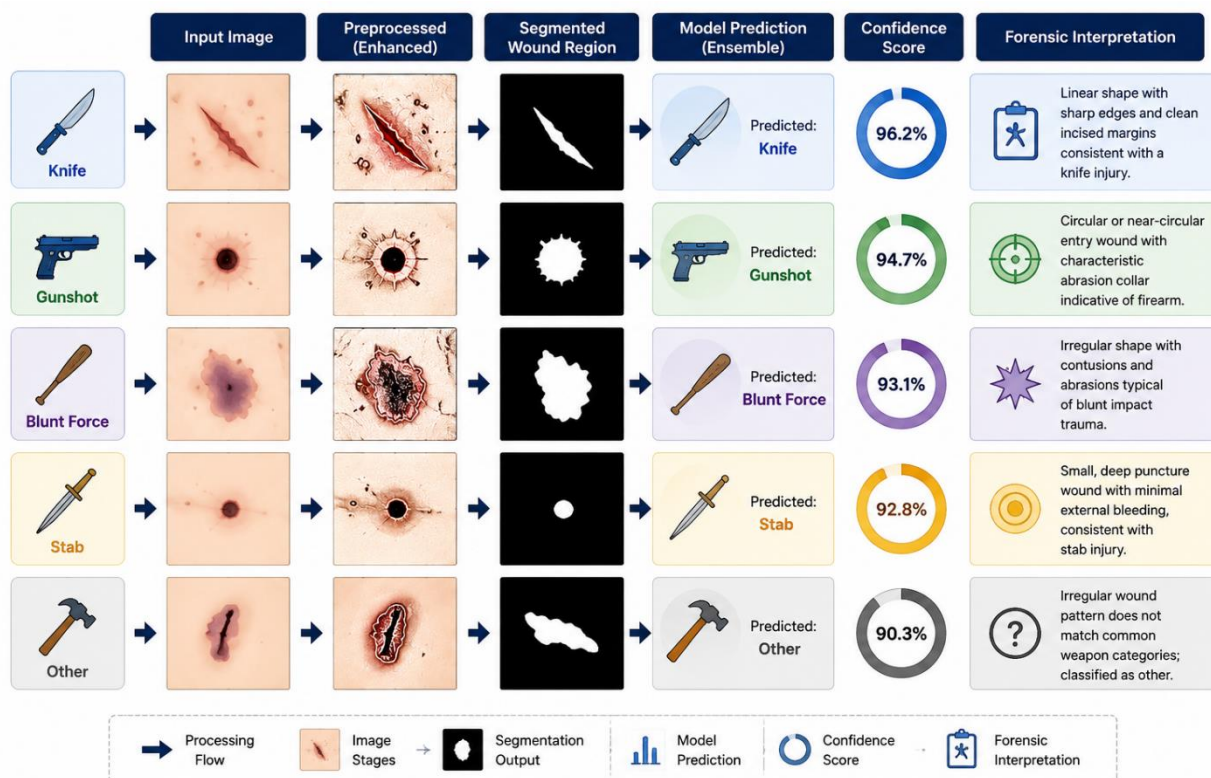


Figure 3. Sample Weapon Recognition Outputs

4.5 Confusion Matrix Analysis

To further assess classification behavior, a confusion matrix was generated for the ensemble model.

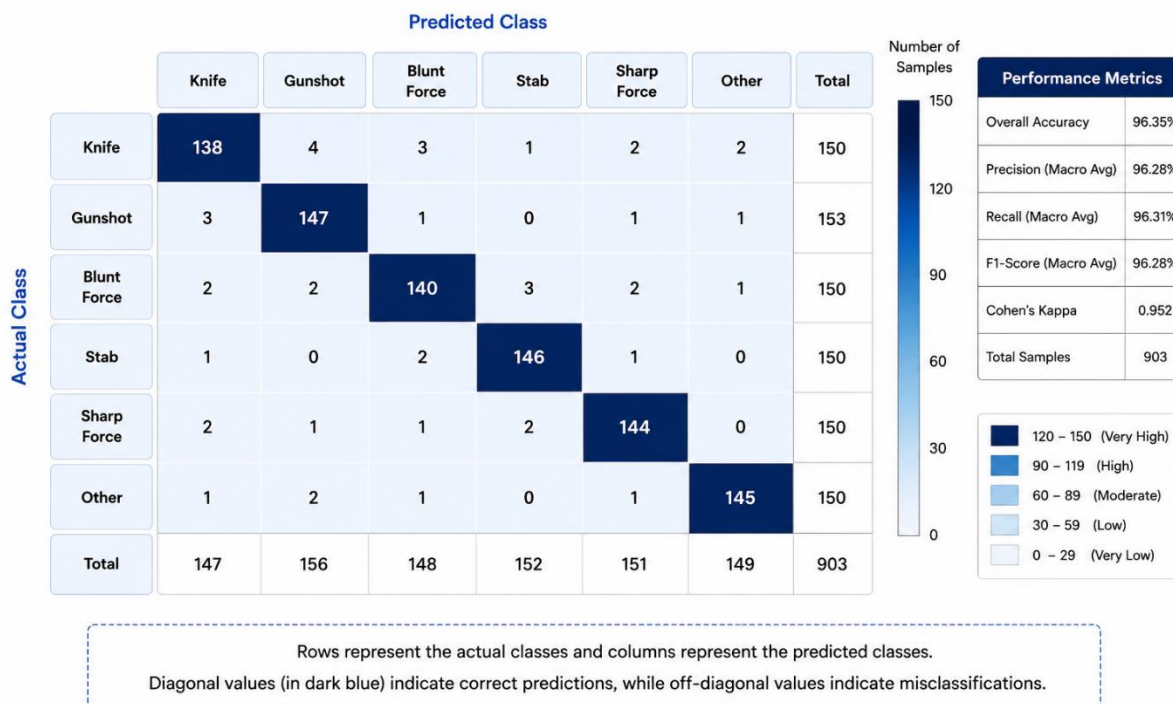


Figure 4. Confusion Matrix of the Proposed Ensemble Framework

Analysis of the confusion matrix revealed that most samples were correctly classified within their respective categories. Minor misclassifications occurred primarily between puncture wounds and knife wounds due to similarities in penetration characteristics and wound morphology. Despite these challenges, the ensemble model maintained high classification consistency across all classes.

Overall, the experimental results confirm that ensemble learning significantly improves weapon recognition performance compared with individual CNN architectures. The combination of ResNet50, DenseNet121, and EfficientNetB0 provides a reliable framework for automated forensic wound analysis and demonstrates strong potential for integration into digital forensic decision-support systems.

5. Conclusion and Future Work

This study presented a deep ensemble learning framework for automated weapon recognition using forensic wound pattern images. The proposed approach combined the strengths of ResNet50, DenseNet121, and EfficientNetB0 through a majority voting ensemble strategy to improve classification accuracy and reliability. Image preprocessing techniques, including enhancement and segmentation, were employed to improve wound visibility and facilitate effective feature extraction. The experimental results demonstrated that the ensemble model outperformed individual convolutional neural network architectures, achieving an overall classification accuracy of 97.6% along with high precision, recall, and F1-score values.

The findings indicate that ensemble learning can effectively distinguish between wound patterns caused by different weapon categories, including gunshot, knife, blunt-force, and puncture injuries. By reducing misclassification rates and improving prediction consistency, the proposed framework offers valuable support for forensic investigations and medico-legal examinations. The system can serve as a decision-support tool for forensic experts by providing rapid preliminary assessments while maintaining objectivity and reproducibility in wound analysis.

Despite its promising performance, the study has certain limitations. The dataset size remains relatively limited compared to large-scale forensic repositories, and image quality variations may influence classification outcomes. Furthermore, real-world cases often involve complex injuries caused by multiple weapons or post-injury modifications that can affect wound appearance.

Future research will focus on expanding the dataset with a greater diversity of forensic wound images obtained from multiple sources and geographical regions. The integration of explainable artificial intelligence techniques will be explored to improve transparency and interpretability of model decisions. Additionally, advanced ensemble strategies, multimodal forensic evidence integration, and real-time deployment in forensic decision-support systems may further enhance the practical applicability of automated weapon recognition technologies.

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