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ANALYZING IMAGES FOR FORENSIC EVIDENCE SUCH AS FINGERPRINTS, FOOTPRINTS AND BLOOD STAINS USING CNN

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Abstract:

Forensic science plays a crucial role in criminal investigations by analyzing evidence to identify suspects and solve crimes. With advancements in digital imaging technology, deep learning techniques, particularly **Convolutional Neural Networks (CNNs)**, have revolutionized forensic evidence analysis by enabling automated and precise identification of patterns in forensic images. This project focuses on developing a **CNN-based forensic evidence analysis system** that processes images of **fingerprints, footprints, and bloodstains** to assist in criminal investigations. Traditional forensic examination methods are often manual, time-consuming, and prone to human error. To overcome these challenges, our system leverages deep learning models trained on three different datasets containing **fingerprints, footprints, and bloodstains**. The system works by analyzing an input forensic image and comparing it with an existing database. If a match is found, the system identifies the individual as a **potential suspect**; otherwise, the person is classified as **not registered in the database**. This approach enhances the efficiency, accuracy, and scalability of forensic investigations by reducing dependency on manual examination. Our results demonstrate the effectiveness of **CNN-based forensic analysis** in crime detection, highlighting its potential in law enforcement applications. However, challenges such as dataset quality, model interpretability, and variations in forensic evidence remain areas for future improvement.

Keywords: Low Light Image Enhancement, Deep Learning, Image Enhancement, Low Light Vision, Dark Image Processing, Low light image restoration, neural networks for low light, enhancing visibility in low light image, denoising, image dehazing, noise reduction.

1. INTRODUCTION

Forensic science plays a pivotal role in criminal investigations by providing crucial evidence that aids in suspect identification and crime resolution. With the rapid advancement of technology, traditional forensic analysis methods are increasingly being supplemented by digital tools, enhancing both accuracy and efficiency. Among these innovations, Convolutional Neural Networks (CNNs), a subset of deep learning, have emerged as powerful tools for processing complex forensic image data.This paper explores the application of CNNs in forensic image analysis, focusing on three critical types of evidence: fingerprints, footprints, and bloodstains. Traditional forensic techniques often rely on manual examination, which can be time-consuming, error-prone, and difficult to scale. In contrast, CNN-based automated systems offer a transformative approach, leveraging deep learning for efficient feature extraction, classification, and pattern recognition.The proposed system utilizes CNNs to analyze forensic datasets and identify individuals based on provided image inputs. When an image is processed, the system determines whether the individual is registered in a forensic database. If a match is found, the person is identified as a potential suspect; otherwise, they are classified as normal. By addressing limitations in conventional forensic methodologies, this framework highlights the potential of CNNs to revolutionize forensic science through automation, reduced human

2. LITERATURE SURVEY

Kavipriya and Muthukumar (2019) [1] conducted a study on biometric authentication using Convolutional Neural Networks (CNNs) for finger knuckle print identification. Their research demonstrated that deep learning models enhance the speed and accuracy of matching biometric prints, making them more reliable for authentication purposes. The study emphasized CNN's role in improving precision in biometric recognition.

Zhang, Chen, and Wang (2020) [2] explored the application of CNN architectures in intrusion detection. Their study provided foundational insights into how CNNs can be leveraged for forensic image analysis and cybersecurity applications. By implementing CNN-based models, they demonstrated improved threat detection and anomaly recognition, making intrusion detection systems more robust and efficient.

Gao, Wang, and Song (2021) [3] focused on domain adaptation techniques in CNNs for industrial control networks. Their research tackled the challenges of handling diverse datasets in forensic image analysis, particularly where image variability is a concern. They proposed methods to enhance CNN adaptability across different industrial environments, ensuring consistent performance in real-world scenarios.

Ma, Long, et al. (2022) [4] developed a Self-Calibrated Illumination (SCI) learning framework for fast, flexible, and robust brightening of images in real-world low-light scenarios. They established a cascaded illumination learning process with weight sharing, reducing computational costs while maintaining efficiency. Their model enhances low-light image processing by defining an unsupervised training loss, enabling adaptability across general scenes. Extensive experiments demonstrate its superiority in both quality and efficiency, with applications in low-light face detection and nighttime semantic segmentation.

Wang, Yufei, et al. (2022) [5] investigated modeling the one-to-many relationship in low-light image enhancement using a normalizing flow model. They introduced an invertible network that conditions low-light images/features to map the distribution of normally exposed images into a Gaussian distribution. Their method improves illumination, reduces noise and artifacts, and enhances color quality, achieving better performance in benchmark datasets.

Hai, Jiang, et al. (2023) [6] proposed a Retinex-based Real-low to Real-normal Network (R2RNet) for low-light image enhancement, consisting of three subnets: Decom-Net, Denoise-Net, and Relight-Net. These subnets handle decomposition, denoising, contrast enhancement, and detail preservation. Unlike traditional methods trained on synthetic images, they constructed the Large-Scale Real-World (LSRW) dataset, enabling better generalization in real-world low-light conditions. Their approach significantly improves high- level visual tasks like face detection in low-light settings.

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Xiong, Wei, et al. (2022) [7] addressed low-light image enhancement in an unsupervised manner by decoupling illumination enhancement and noise suppression. They introduced a two-stage model, where the illumination-aware denoising model ensures noise removal based on illumination conditions. Their model outperforms existing unsupervised methods in both illumination enhancement and noise reduction through extensive evaluations on real-world low-light datasets.

Zheng, Shen, et al. (2022) [8] developed a semantic-guided zero-shot low-light enhancement network (SGZ), which does not require paired images, unpaired datasets, or segmentation annotation. They designed an enhancement factor extraction network using depthwise separable convolution for estimating pixel-wise light deficiencies.
Their approach includes a recurrent image enhancement network that progressively enhances low-light images while preserving semantic information. The proposed method outperforms previous state-of-the-art techniques, with applications in low-light detection and segmentation.

Wu, Yirui, et al. (2022) [9] introduced an edge computing and multi-task driven framework for real-time image enhancement and object detection. Their framework consists of two stages: a cloud-based enhancement phase and an edge-based detection phase. The cloud-based enhancement dynamically improves low-light images, while the edge-based detection enhances feature extraction for more accurate object detection in low-light environments. Experimental results show significant improvements in mobile multimedia applications and forensic image **processing**.

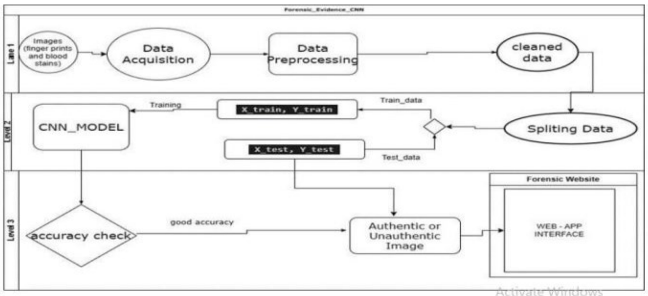
3. PROPOSED METHODOLOGY

This proposed methodology focuses on enhancing forensic identification using deep learning, specifically Convolutional Neural Networks (CNNs). The primary objective of this model is to improve the accuracy and efficiency of forensic investigations by analyzing fingerprints, footprints, and bloodstains with minimal human intervention. Traditional forensic methods rely on manual feature extraction, which can be time-consuming and prone to human error. In contrast, this deep learning-based approach enables automatic pattern recognition, making forensic analysis more reliable and precise. By leveraging CNNs, the system can extract intricate features, classify forensic evidence, and generate automated reports, ultimately reducing investigation time and enhancing crime-solving accuracy.

Figure 1: Proposed System Architecture

The proposed methodology consists includes the following key components:

- **Input Data Acquisition**: The system acquires forensic evidence images, including fingerprints, footprints, and bloodstains, from forensic databases and real-world crime scenes. The images are processed in various formats such as JPEG, PNG, and TIFF to maintain compatibility across forensic tools.
- **Data Preprocessing**: The acquired images undergo preprocessing using techniques like Histogram Equalization and Gaussian Filtering to enhance clarity. Noise is reduced through Median Filtering, and segmentation methods such as Thresholding and Edge Detection (Canny, Sobel) are applied to isolate key patterns for better feature extraction.
- **Dataset Splitting and Augmentation**: The dataset is divided into training, validation, and testing sets to ensure robust model performance. Data augmentation techniques, including flipping, rotation, contrast adjustment, and random cropping, improve model generalization and prevent overfitting.
- **Feature Extraction using Deep Learning**: A CNN-based model automatically extracts crucial forensic features such as fingerprint ridges, footprint impressions, and bloodstain spread patterns. Multi-layer convolutional processing enhances the detection of intricate details, improving classification accuracy and ensuring reliable forensic identification.
- **CNN Model Training and Optimization**: Various CNN architectures, including ResNet50, VGG16, and EfficientNet, are trained using transfer learning to optimize feature extraction. The best-performing model is selected based on accuracy, loss function performance, and generalization capability
- **Forensic Classification and Identification**: The system classifies forensic evidence based on biometric uniqueness and pattern similarities. It differentiates individuals using fingerprint ridge minutiae, footprint pressure points, and bloodstain impact analysis. Advanced matching algorithms, such as Siamese Networks and Triplet Loss, improve forensic identification accuracy while minimizing false positives.



- Accuracy Validation and Model Performance Evaluation: The trained model undergoes rigorous evaluation using accuracy metrics, including Precision, Recall, F1-Score, and a Confusion Matrix. Misclassified instances are analyzed to improve feature extraction and classification strategies.
- Real-Time Classification and Web-Based Deployment: The trained model is integrated into a Flask-based web application that allows forensic experts to upload images for real-time classification. The system returns results with confidence scores, providing immediate insights for forensic investigations.
- Forensic Report Generation: The system generates detailed forensic reports, including matched fingerprint/footprint profiles, suspect identification likelihood, crime scene pattern analysis, and probability scores for forensic matches. These reports assist law enforcement agencies in making informed decisions based on automated forensic evidence classification.
- Scalability and System Adaptability: The system is designed to handle large-scale forensic datasets efficiently, ensuring scalability for future applications. Domain adaptation techniques enhance model adaptability to different forensic environments, improving reliability across diverse case studies.

Applications:
The proposed system can be applied in multiple forensic domains, including:

- Criminal Investigations – Enhancing evidence analysis for law enforcement.
- Legal Proceedings – Providing accurate forensic reports to support trials.
- Missing Persons Identification – Matching forensic evidence to known individuals.

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Advantages:

This CNN powered forensic system offers several benefits:

- **Higher Accuracy and Efficiency**: CNN models automatically learn intricate forensic patterns, reducing errors and improving identification precision.
- **Scalability with Large Datasets**: The system efficiently processes and analyzes extensive forensic databases.
- **Robust Performance in Real-World Conditions**: Deep learning models adapt to different environmental factors, ensuring reliable forensic analysis.
- **Automation Reduces Human Error**: Eliminates manual feature extraction, minimizing bias and improving objectivity.
- **Interactive Forensic Dashboard**: Provides forensic analysts with a dashboard for reviewing and comparing forensic results effectively.
- **Enhanced Feature Extraction:** CNNs automatically extract deep hierarchical features, capturing minute forensic details that traditional methods might miss.
- **Real-Time Processing:** Optimized deep learning models enable quick forensic analysis, making them suitable for time-sensitive applications like crime scene investigations.
- **Cross-Domain Adaptability:** CNN models can be fine-tuned to analyze forensic data across different domains, such as biometric authentication, intrusion detection, and industrial security.
- **Improved Image Restoration:** Deep learning techniques enhance low-quality forensic images by reducing noise, correcting illumination, and improving resolution.
- Advanced Pattern Recognition: CNNs detect complex patterns in forensic data, aiding in fingerprint, face, and knuckle print identification with greater accuracy.
- Multimodal Analysis: Deep learning models integrate data from multiple sources (e.g., images, videos, and sensor data) for comprehensive forensic evaluations.
- Anomaly and Fraud Detection: CNN-based models identify irregularities and potential forgeries in forensic images, improving fraud detection in security systems.
- Adaptive Learning: Models continuously improve as more forensic data is processed, leading to better decision-making and enhanced predictive capabilities.

4. EXPERIMENTAL ANALYSIS

The experimental analysis involved testing the deep learning-based forensic classification system by uploading images of fingerprints, bloodstains, and footprints. The model processed these images and determined whether the forensic evidence was **authenticated** (genuine) or **unauthenticated** (fabricated or misleading). The system leveraged a CNN-based approach, trained on six distinct categories: authenticated and unauthenticated fingerprints, footprints, and bloodstains. By analyzing intricate forensic patterns, the model provided classification results with high confidence scores, helping investigators verify the credibility of evidence and identify potential criminals.

Figure 2: Home Page

Figure3: Uploading Image

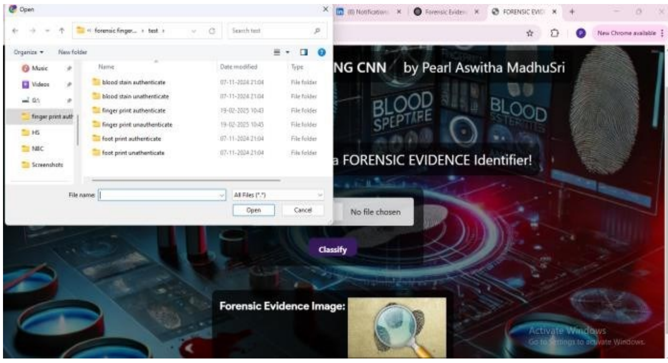

Figure 4: Detected blood stain as Authenticate

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Figure 5: Detected Footprint as Authenticate

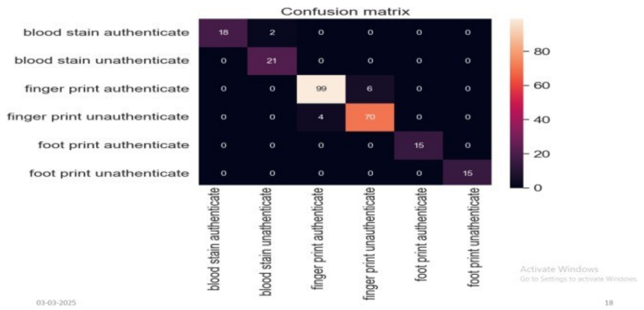

Figure 6: Confusion Matrix

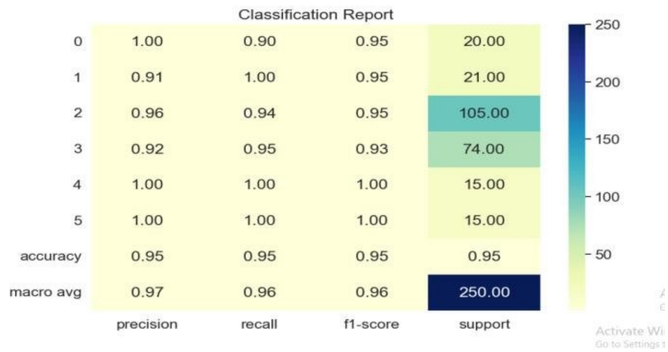

Figure 6: Classification Report

To evaluate its performance, a **confusion matrix** and a **classification report** were generated for each category: **authenticated and unauthenticated fingerprints, footprints, and bloodstains**. The **classification report** included key performance metrics such as **precision, recall, F1-score, and accuracy**, providing insights into the model's effectiveness in forensic evidence validation. The **confusion matrix** highlighted the correct and misclassified instances, helping to identify patterns in errors. The results demonstrated that the model achieved **high accuracy** in distinguishing authentic from inauthentic forensic samples, reducing false positives and false negatives, and improving forensic identification reliability..

5. CONCLUSION

This ground-breaking work signifies a substantial leap forward in the domain of forensic evidence analysis using deep learning. By employing Convolutional Neural Networks (CNNs), the proposed system revolutionizes the identification and authentication of forensic traces such as bloodstains, fingerprints, and footprints. The integration of deep learning models, including ResNet50, VGG16, and Efficient Net, has significantly enhanced classification accuracy, reduced human dependency, and accelerated forensic investigations. This approach ensures that forensic evidence processing is not only more efficient but also more reliable and objective.

A key highlight of this system lies in its adaptability and robustness in forensic analysis. By incorporating techniques such as transfer learning, data augmentation, and real-time classification through a Flask-based web interface, the solution provides a scalable and efficient forensic tool. Furthermore, the implementation of quality assessment metrics ensures that the system maintains high precision and consistency across diverse forensic environments. These advancements collectively contribute to a more automated and streamlined forensic workflow, minimizing manual errors and enhancing investigative outcomes.

The far-reaching impact of this forensic evidence analysis system extends across multiple domains, significantly benefiting crime investigation agencies, law enforcement, and forensic laboratories. The automation of forensic classification expedites suspect identification and strengthens legal proceedings by providing objective and data-driven evidence. Additionally, its potential application in digital forensics allows for seamless integration with crime databases, aiding in the cross-referencing of forensic traces and improving criminal case resolution rates. This advancement reinforces forensic credibility and enhances the overall efficiency of the judicial system.

While the current system demonstrates remarkable success, several promising avenues exist for future research and development. One critical enhancement involves the integration of higher-resolution image processing techniques, such as AI-driven super-resolution, to further refine forensic trace differentiation. Additionally, multi-modal forensic analysis, combining fingerprint patterns with thermal imaging or spectroscopic data, could provide a more comprehensive evaluation. The development of real-time mobile applications would further empower law enforcement to conduct on-site forensic assessments, ensuring faster decision-making and improved case handling.

Looking ahead, adaptive AI models capable of continuous learning from new forensic cases will significantly enhance system performance. Techniques such as federated learning will enable secure training across multiple law enforcement agencies without compromising sensitive forensic data. Furthermore, automation in forensic reporting through AI-assisted summaries will help investigators analyze key findings more efficiently. By implementing these advancements, forensic evidence analysis will continue to evolve, solidifying AI's role as an indispensable asset in modern crime-solving methodologies.

Blockchain integration will ensure secure, tamper-proof forensic data storage. Multimodal AI analysis, including voice and gait recognition, will enhance identification accuracy. Real-time AI updates will improve investigative speed and reliability.

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