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Scanning Methods for Detecting External Injuries

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ABSTRACT—

External injuries, especially those caused by animal attacks such as dog bites, pose serious risks to human health. Timely and accurate detection is critical for effective treatment, legal documentation, and infection control. This paper explores modern full-body scanning technologies that can assist in identifying external injuries. The study reviews visual imaging, thermal scanning, 3D surface reconstruction, and ultrasound techniques. We present a comprehensive diagnostic workflow, discuss real-world applications in clinical and forensic fields, and evaluate the challenges and future scope of this technology. Our research advocates the integration of artificial intelligence and multi-modal scanning to enhance injury detection and treatment outcomes.

I. Introduction

In recent years, injuries caused by dog bites have become a growing public health issue, with implications ranging from medical to legal domains. These injuries often involve visible and hidden trauma that may go undetected without the aid of advanced imaging tools. Traditional examination methods, including manual inspection and standard photography, are insufficient for thorough injury analysis. There is a growing need for automated systems that can scan the entire body and detect all types of external injuries, including bite marks, abrasions, bruises, and swelling. In this context, full-body scanning technologies play a crucial role. This paper aims to explore these technologies and propose an integrated system for external injury assessment.

BASIC FUNCTIONALITIES OF FULL-BODY SCANNING FOR INJURY DETECTION

Full-body scanning combines multiple imaging modalities to detect injuries in a non-invasive and comprehensive manner. The basic functionalities include:

- High-Resolution Imaging: Captures clear, detailed images of the skin surface
- Thermal Scanning: Identifies temperature anomalies that indicate inflammation.
- 3D Scanning: Reconstructs the body surface for depth analysis of wounds.
- Ultrasound: Detects internal injuries and hematomas not visible externally.
- AI Integration: Classifies injury types and provides automatic annotation.

These technologies provide immediate and objective injury assessment, facilitating timely medical and forensic decisions.

PROS OF FULL-BODY SCANNING FOR INJURY DETECTION

1. **Non-Invasive and Painless Procedure**

Scanning methods, such as 3D imaging or thermal

scanning, do not require physical contact, making them comfortable and safe for patients.

2. **Faster Diagnosis and Documentation**

These methods quickly capture and record injuries, enabling rapid assessment and reducing time for

medical and legal processing.

3. **High Accuracy in Injury Detection**

Advanced imaging provides detailed visuals,

improving the ability to detect subtle or complex injuries like dog bite marks.

4. **Real-Time Analysis with AI Support**

AI algorithms can instantly analyze scan data, helping clinicians make quick, informed decisions on injury severity and type.

5. **Suitable for Emergency and Forensic Use**

These tools are effective in urgent care settings and in forensic investigations to document and evaluate injuries accurately.

6. **Enhances Telemedicine Capabilities**

Scanned images can be shared remotely with

specialists, supporting virtual consultations and expert reviews.

7. **Improves Legal Evidence Collection**

High-resolution, time-stamped scans serve as objective and reliable evidence in legal and insurance cases involving external injuries.

CONS OF INJURY DETECTION USING MACHINE LEARNING

1. **Narrow Class Coverage**: The current system focuses on five external injury types, leaving out rare or internal injuries.
2. **Visual Similarity Issues**: Certain injury types (e.g., lacerations vs. bite marks) may appear visually similar, leading to misclassification.
3. **Lighting and Image Quality Sensitivity**: Performance may degrade in poorly lit or low- resolution images.
4. **Localization Challenges**: Accurately detecting the exact wound region may be difficult for small or obscured injuries.
5. **Language and Accessibility**: Application usage may be limited by language support or lack of digital infrastructure in some regions.

DATA PROPAGATION IN INJURY CLASSIFICATION

Several researchers have proposed computer vision solutions for medical diagnostics. For example, Ferentinos (2018)

demonstrated the power of CNNs in plant disease detection— a concept we adapted for trauma identification. In our model, we used a custom CNN design optimized for medical

imagery, incorporating dropout, batch normalization, and global average pooling for enhanced performance.

To improve accuracy for dog bite detection specifically, we applied a submodule trained on tooth-arc patterns and wound geometry, enhancing detection even under occluded or

partially healed conditions.

MODEL ARCHITECTURE

1. ARCHITECTURE DESIGN CONSIDERATIONS

- **Efficiency**: Lightweight enough for real-time use on standard computing devices.
- **Robustness**: Designed to handle diverse environmental factors such as lighting and skin tone.
- **Prevention of Overfitting**: Included dropout layers and image augmentation.
- **Interpretability**: Used Grad-CAM to visualize predictions.

2. DESIGN RATIONALE

1. **Batch Normalization**: Accelerated training and reduced internal covariate shift.
2. **Global Average Pooling**: Reduced overfitting by minimizing parameters.
3. **Progressive Filter Depth**: Increased complexity to capture finer details in wound texture.
4. **Dual Dropout Layers**: Improved generalization across datasets.

USING MACHINE LEARNING

3. TRAINING STRATEGY

The dataset used in this study was curated from open-access medical repositories, veterinary sources, and forensic databases. It consists of five primary categories.

1. 20 epochs at learning rate 0.001, batch size 32.
   - Abrasions: 1,200 images
   - Lacerations: 1,000 images
   - Contusions: 1,000 images
   - Puncture Wounds: 1,200 images
   - Dog Bite Wounds: 1,100 images

2. Fine-tuned for 10 more epochs at 0.0001 learning rate

3. Adaptive dropout for reducing training-validation gap

4 .HARDWARE AND SOFTWARE ENVIRONMENT

The training and evaluation of the injury detection model were

To simulate real-world conditions, we included images taken under diverse lighting, angles, and camera resolutions.

Additionally, 500 images were gathered from hospital

emergency departments and annotated by trauma specialists and forensic experts.

SPECIFIC APPROACHES FOR INJURY CLASSIFICATION

conducted on a high-performance workstation equipped with the following hardware and software specifications:

- **Hardware Configuration:**
  - RAM: 32 GB DDR4
  - Processor: Intel Core i7-10700K @ 3.80GHz
  - Graphics Processing Unit (GPU): NVIDIA GeForce RTX 3080 with 10GB VRAM
- **Operating System:**
  - Ubuntu 20.04 LTS (64-bit)
- **Software and Libraries:**
  - Programming Language: Python 3.8
  - Deep Learning Framework: TensorFlow 2.6
  - High-Level API: Keras 2.6
  - GPU Acceleration Libraries:
    - CUDA Toolkit 11.2
    - cuDNN 8.1

This setup provided a robust environment for model training, real-time inference testing, and hyperparameter tuning, enabling the model to process high-resolution injury images efficiently

and accurately.

5 . HYPERPARAMETER OPTIMIZATION

To identify the optimal configuration for training the injury classification model, a comprehensive grid search was

conducted across several key hyperparameters. The goal was to achieve the best trade-off between model accuracy,

generalization capability, and training efficiency. The following combinations were tested:

- **Learning Rates:**

o 0.01

o 0.001

o 0.0001

- **Batch Sizes:**
  - 16
  - 32
  - 64
- **Dropout Rates:**
  - 0.3
  - 0.5
  - 0.7
- **Optimizers:**
  - Adam
  - RMSprop
  - SGD (with momentum)

The final model achieved optimal performance with a learning rate of 0.001, batch size of 32, and dropout rate of 0.5, using the Adam optimizer. This configuration resulted in a well-

regularized model with high validation accuracy and minimal overfitting across training epochs.

6. IMPLEMENTATION DETAILS

- Loss: Categorical cross-entropy
- Optimizer: Adam with early stopping (patience = 5)
- Dropout: 0.5 in dense layers

NETWORK STRUCTURE

The network consists of four convolutional blocks followed by fully connected layers.

.The model architecture is detailed in Table 1.

Layer Type	Output Shape	Parameters	Notes
Conv2D (64 filters)	(125, 125, 64)	18,496	Initial feature extraction
BatchNorm	(125, 125, 64)	256	Stabilizes and accelerates training
ReLU	(125, 125, 64)	0	Activation function
MaxPooling (2×2)	(62, 62, 64)	0	Downsampling
Conv2D (128 filters)	(60, 60, 128)	73,856	Extraction of deeper features
BatchNorm	(60, 60, 128)	512	Normalizes feature maps
ReLU	(60, 60, 128)	0	Activation
MaxPooling (2×2)	(30, 30, 128)	0	Reduces spatial resolution
Conv2D (128 filters)	(28, 28, 128)	147,584	Final feature extraction
BatchNorm	(28, 28, 128)	512	Normalization
ReLU	(28, 28, 128)	0	Non-linearity
MaxPooling (2×2)	(14, 14, 128)	0	Further downsampling
Global Average Pooling	(128)	0	Feature aggregation

Dropout (rate = 0.5)	(128)	0	Regularization to prevent overfitting
Dense (fully connected)	(512)	66,048	High-level feature abstraction
BatchNorm	(512)	2,048	Training normalization
ReLU	(512)	0	Activation function
Dropout (rate = 0.5)	(512)	0	Regularization layer
Output Dense (Softmax)	(5)	1,539	Final classification output

RESEARCH EXTENSION

1. **Pre-Symptomatic Detection**: Use infrared or hyperspectral imaging to identify inflammation or internal bleeding before visible symptoms appear.
2. **Cross-domain Learning**: Extend the model to detect injuries in animals, useful for veterinary and wildlife monitoring.
3. **Explainable AI (XAI)**: Improve interpretability by combining visual explanations (e.g., Grad-CAM) with simple text summaries of AI decisions.
4. **Impact Assessment**: Test the system in hospitals to measure its effect on diagnostic accuracy, time efficiency, and patient outcomes.
5. **Severity Grading**: Add the ability to classify injuries by severity (mild, moderate, severe) to aid in medical triage.
6. **EMR Integration**: Automatically log detected injuries into electronic medical records for better documentation.
7. **Progress Tracking**: Compare images over time to monitor healing or detect infection.
8. **Federated Learning**: Train models across hospitals without sharing patient data, improving accuracy while maintaining privacy.

FUTURE SCOPE

1. **Real-time Integration**: Implement IoT-enabled wound scanners for emergency units and disaster zones.
2. **Multi-modal Analysis**: Combine video, thermal, and text data for comprehensive trauma assessment.
3. **Crowdsourced Data Collection**: Create mobile apps to collect wound data from users for training more diverse models.
4. **Legal and Ethical Integration**: Add evidence tracking modules for admissibility in legal investigations.

CONCLUSION

This is different from other papers as children don't tell their parents about the injuries they got as they think they'll beaten them up so this small identification device which is portable

also may help parents to get to know about the injury in a easy manner.This research presents a novel application of deep

learning in the field of medical and forensic injury detection, with a focus on dog bite wounds. By leveraging CNNs and

image processing techniques, we developed a system capable of classifying external injuries with high accuracy. The model's real-world applicability and extendibility make it a promising solution for rapid, consistent, and objective injury assessment in diverse environments.

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