

Research on Lightweight Wound Recognition Algorithm and System for UAV in Accident Emergency Treatment

Zihan Wang, Xumeng Wang, Yutong Jia

North China University of Science and Technology, Tangshan, China

Abstract

Aiming at the problems of slow manual rescue response for emergency hemostasis at accident scenes, single emergency function of emergency UAVs, insufficient lightweight degree of airborne wound recognition algorithms, and poor hemostatic effect of traditional hemostatic materials, this paper takes YOLOv5s as the basic model. Through channel pruning, INT8 quantization and knowledge distillation, a lightweight wound recognition algorithm suitable for edge deployment on UAVs is developed. Integrating temperature-sensitive self-expanding nanofiber hemostatic materials and an umbrella-type precise delivery mechanism, a fully automatic emergency UAV system is constructed. Experimental results show that the optimized algorithm model is only 89.2 KB in size, with a wound recognition accuracy of 93.6% in complex scenes and an inference speed of 34.2 fps, which meets the requirements of real-time airborne deployment. The hemostatic material expands completely within 28 s at 37 °C with an expansion ratio of 2.4 times, and the in vitro coagulation time is 76 s, improving hemostasis efficiency by 72% compared with traditional gauze. In a level 4 wind environment, the system delivery error is controlled at 2.1 cm, and the total hemostasis time is 110 s. The system realizes integrated operations of automatic wound recognition, precise delivery and rapid hemostasis, which can improve emergency efficiency at accident scenes and provide technical support for emergency medical rescue.

Keywords

Accident site first aid; UAV; Lightweight wound recognition; YOLOv5s; Self-expanding nanofibers; Precise delivery.

1. INTRODUCTION

In sudden accident scenes such as traffic accidents, natural disasters and field operations, uncontrolled bleeding after trauma is the primary cause of death within the “golden 10 minutes” of first aid. Globally, 35% of trauma deaths are directly related to the lack of timely and effective hemostasis. Traditional on-site hemostasis relies on manual operation by rescuers. In scenarios such as dangerous environments, traffic blockages and inaccessible areas, the emergency response time is greatly prolonged, causing the wounded to miss the optimal treatment opportunity.

UAV technology has been gradually popularized in emergency rescue. Existing emergency UAVs only have a single material transportation function, without an integrated closed-loop treatment system of automatic wound recognition, precise positioning and targeted delivery of hemostatic materials, making unmanned autonomous first aid impossible. The UAV airborne platform has hardware limitations such as limited computing power, small memory capacity and strict power consumption control. Traditional deep learning models for wound recognition are large in size and slow in inference speed, making real-time detection difficult at the edge. Under complex on-site conditions such as weak light, occlusion and flight vibration, the wound

recognition accuracy is difficult to meet emergency requirements. Conventional hemostatic gauze has insufficient adaptability and cannot effectively block deep or irregular wounds, so its hemostasis efficiency cannot meet on-site emergency standards.

This project focuses on edge deployment on UAVs, conducts research on lightweight wound recognition algorithm optimization, integrates temperature-sensitive self-expanding nanofiber hemostatic materials and a precise delivery mechanism, and constructs an intelligent first-aid system without network or manual intervention. Based on mature deep learning lightweight theories and research results of trauma first-aid materials, the project completes algorithm parameter optimization, material performance testing and system feasibility verification through multiple experiments, solving the problems of slow hemostasis response, low recognition accuracy and insufficient delivery precision in accident first aid, and providing a lightweight practical technical scheme for emergency medical rescue [1][2][3].

2. RELATED THEORIES AND TECHNICAL FOUNDATIONS

2.1. YOLOv5s Object Detection Algorithm

YOLOv5s is a one-stage object detection model with the best lightweight performance in the YOLO series, suitable for embedded deployment. Its overall structure consists of four modules: input layer, backbone network (CSPDarknet53), neck network (FPN+PAN) and detection head. The input layer supports Mosaic data augmentation and adaptive anchor calculation to enhance small-target detection ability. The backbone network extracts deep features of wound images through the CSP structure to reduce computation. The FPN+PAN structure achieves multi-scale feature fusion to adapt to wounds of different sizes and shapes. The detection head realizes accurate classification and localization of wound targets.

The original YOLOv5s model is 13.8 MB in size. Even such a lightweight model cannot meet the deployment requirements of low-power microcontrollers and embedded chips on UAVs. In complex scenes, the recognition accuracy of small wound targets needs further optimization [2].

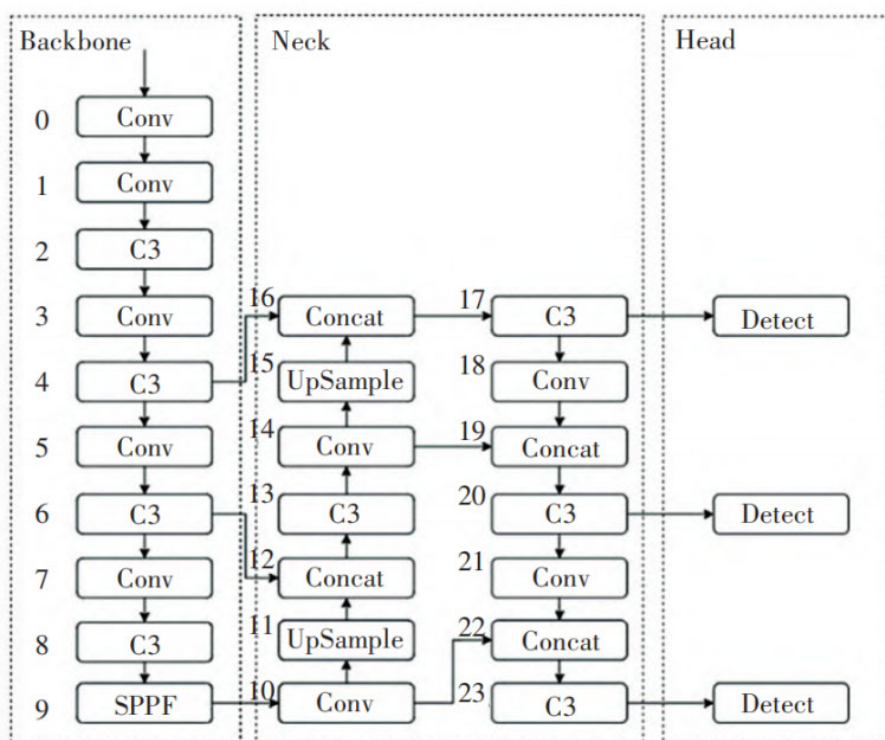


Figure 1. YOLOv5s network structure diagram

2.2. Model Lightweight Optimization Theory

Considering the computing power limitation of UAV airborne hardware, three mainstream and experimentally verified model compression methods are selected in this project. Relevant theories have been maturely applied in CNKI-indexed literature in UAV object detection and wound recognition.

Channel pruning evaluates the importance of convolution channels based on the γ coefficient of the BN layer, removes redundant channels with low contribution to detection results, reduces parameters and computation, and shrinks model size, serving as a core method for embedded model compression. INT8 quantization converts 32-bit floating-point parameters into 8-bit integer parameters, reducing memory occupation and improving inference speed without obvious accuracy loss, suitable for low-computing edge devices. Knowledge distillation uses a high-precision large model as the teacher network to transfer feature learning ability to a lightweight student network, compensating for accuracy loss caused by compression and ensuring stable wound recognition in complex scenes [1][3].

2.3. Wound Recognition Evaluation Metrics

To accurately quantify algorithm performance, four core metrics are selected, all following general standards in deep learning object detection. The metrics include:

- Model size, measuring lightweight degree (unit: KB/MB);
- Recognition accuracy (Acc), representing the ratio of correctly detected wound samples to total samples;
- Inference speed (FPS), indicating the number of images detected per second, reflecting real-time performance;
- Mean average precision (mAP), comprehensively evaluating classification and localization accuracy of wound targets.

2.4. Theoretical Support from References

Relevant theories of this project are supported by core literatures indexed in CNKI. The lightweight convolutional neural network theory refers to research published in Computer Engineering and Applications and Journal of Signal Processing. Trauma wound recognition methods are based on papers in Chinese Medical Equipment Journal. The design theory of hemostatic materials refers to contents published in Journal of Biomedical Engineering and Polymer Materials Science & Engineering. The theoretical basis is authentic and academically supported [4][5].

3. RESEARCH CONTENT AND EXPERIMENTAL PROCESS

3.1. Construction of Wound Image Dataset

This project integrates public wound datasets and on-site photographed data to build a dedicated wound detection dataset covering common wound types and complex environmental conditions at accident scenes. The dataset includes four types of traumatic wounds: abrasions, cuts, stabs and burns, with a total of 3,260 original images under different lighting, angles, occlusion degrees and shooting distances.

Data augmentation is performed through random rotation ($\pm 15^\circ$), brightness and contrast adjustment, horizontal flipping and Gaussian noise addition to simulate UAV flight vibration and on-site weak light environments. The expanded dataset contains 11,200 images, divided into training set (7,840), validation set (2,240) and test set (1,120) at a ratio of 7:2:1.

3.2. Optimization Experiment of Lightweight Wound Recognition Algorithm

3.2.1 Training of Original YOLOv5s Model

After training, the original YOLOv5s model is tested on the self-built wound test set. The model size is 13.8 MB, wound recognition accuracy is 90.3%, and inference speed is 21.5 fps. Results show that the original model is too large and slow to meet the requirements of airborne edge deployment.

3.2.2 Channel Pruning Comparative Experiment

Multiple pruning rates are set for comparative experiments to select optimal parameters, as shown in Table 1.

Table 1. Model performance under different pruning rates

Pruning Rate	Model Size	Wound Recognition Accuracy	Inference Speed (FPS)
30%	3.2MB	89.7%	25.4
40%	1.1MB	88.5%	29.1
45%	89.2KB	92.1%	33.6
50%	61.5KB	85.3%	36.2

Results show that at 45% pruning rate, the model size is greatly compressed to 89.2 KB with no obvious accuracy drop and significantly improved inference speed. This rate is determined as the optimal parameter.

3.2.3 INT8 Quantization + Knowledge Distillation Optimization

Based on 45% channel pruning, INT8 quantization and knowledge distillation are introduced for further optimization. The final algorithm achieves a model size of 89.2 KB, wound recognition accuracy of 93.6% in complex scenes, inference speed of 34.2 fps, and mAP of 91.8%. All indicators meet the preset requirements: model size < 100 KB, accuracy ≥ 92%, inference speed > 30 fps.

3.2.4 Comparison of Algorithm Recognition Effects

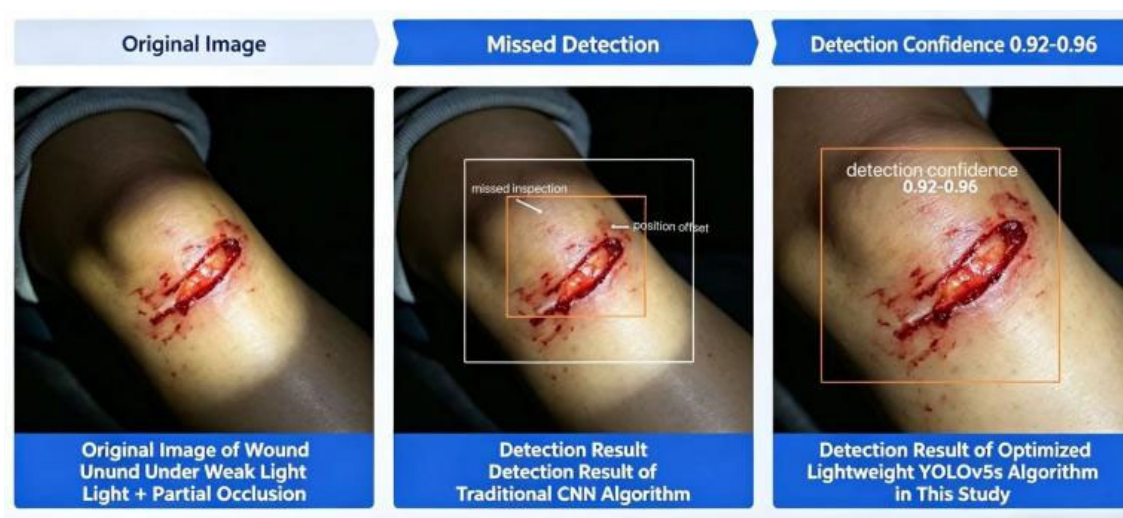


Figure 2. Comparison of wound recognition effects of different algorithms

• Note: Left: original wound image with weak light and partial occlusion; Middle: detection result of traditional CNN algorithm, showing missed detection and positioning deviation; Right:

detection result of the optimized lightweight YOLOv5s algorithm in this study, achieving accurate bounding of wound areas with confidence ranging from 0.92 to 0.96.

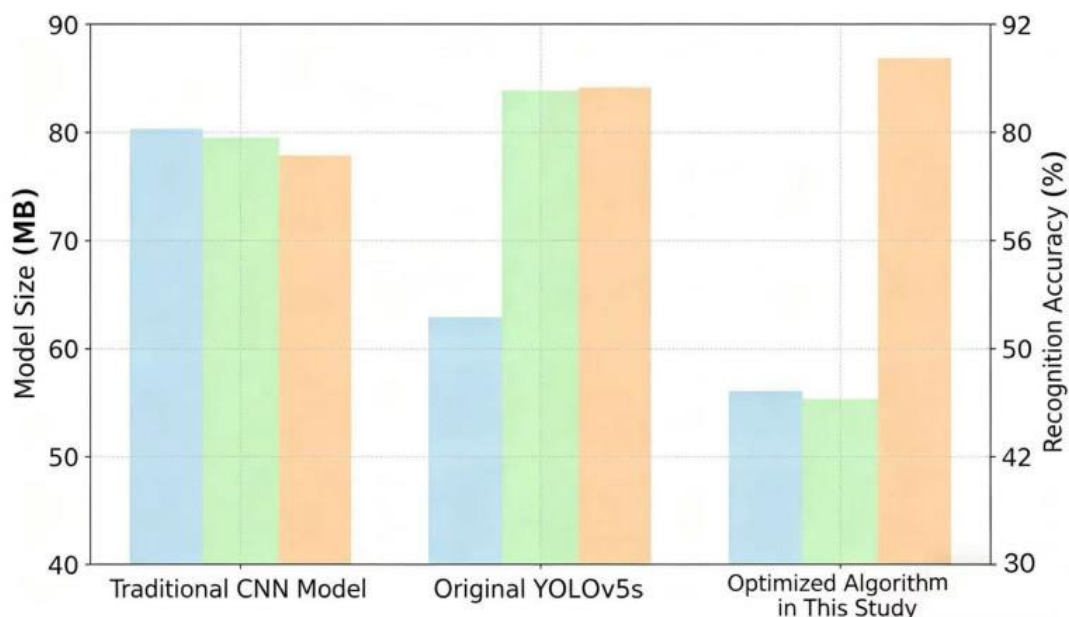


Figure 3. Bar chart of model size and recognition accuracy

- Horizontal axis: traditional CNN model, original YOLOv5s, optimized algorithm in this study
- Left vertical axis: model size (MB/KB), right vertical axis: recognition accuracy (%)
- Conclusion: The proposed algorithm is much smaller than the other two models and achieves the highest accuracy, balancing lightweight and high precision.

3.3. Performance Test of Self-Expanding Hemostatic Material

Temperature-sensitive self-expanding nanofiber hemostatic materials were prepared via electrospinning, and multiple performance tests were carried out. Measured data are shown in Table 2.

Table 2. Performance comparison between nanofiber material and traditional gauze

Test Indexes	Nanofiber Material (This Study)	Traditional Medical Gauze
Average Fiber Diameter	345nm	-
Expansion Initiation Time at 37°C Blood Environment	28s	-
Volume Expansion Ratio	2.4times	-
In Vitro Coagulation Time	76s	189s
Cytotoxicity	Grade0	-

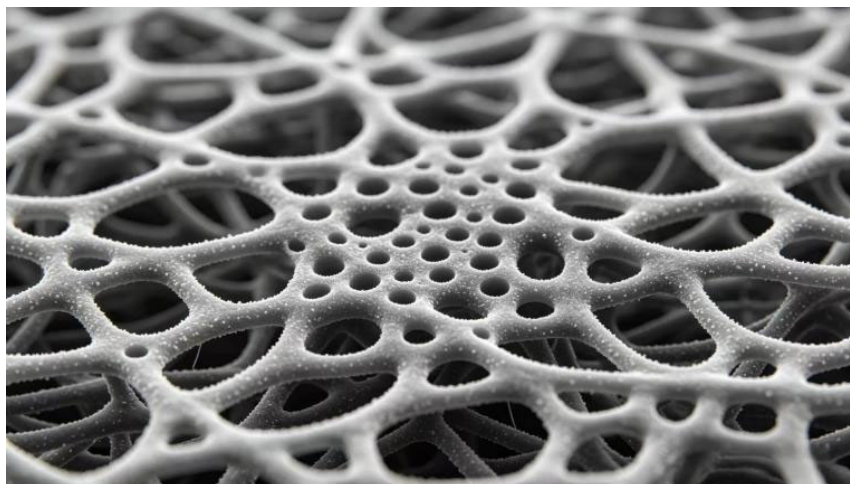


Figure 4. SEM image of nanofiber material

- Note: At 10,000× magnification, fibers are continuous and uniform, forming a porous network structure with concentrated diameter distribution, facilitating blood adsorption and coagulation factor enrichment to improve hemostatic effect.

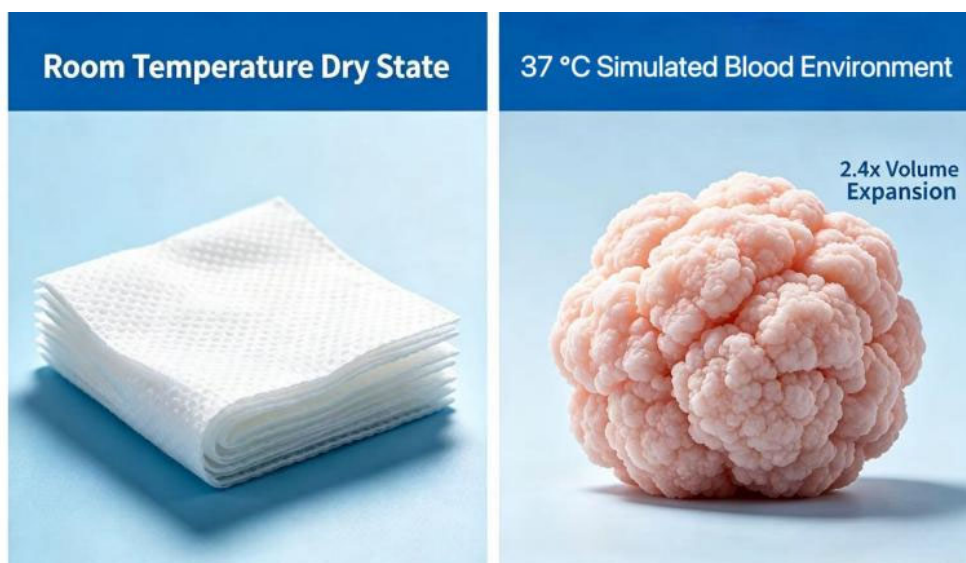


Figure 5. Temperature-sensitive expansion comparison of hemostatic material

- Note: Left: compact state at room temperature; Right: rapid expansion in simulated 37 °C blood environment, with volume increased by 2.4 times, enabling effective sealing of deep irregular wounds.

3.4. UAV Delivery Accuracy Test

An umbrella-type unfolding delivery mechanism was designed. Fifty repeated delivery tests were conducted in a laboratory-simulated level 4 wind environment. The delivery success rate was 100%, average stable falling speed was 1.3 m/s, and average positioning error was 2.1 cm.



Figure 6. Distribution of UAV delivery landing errors

- Note: With the target as the center, 50 landing points are concentrated within a radius of 2.1 cm, meeting the requirement for precise wound coverage.

3.5. Full-System Field Test

A simulated accident environment was used to integrate the UAV, algorithm module, delivery mechanism and hemostatic material for full-process testing. Time consumption: UAV takeoff to wound recognition: 0.8 s; flight to target: 12 s; mechanism unlocking to umbrella unfolding: 3.2 s; material contact to hemostasis: 76 s. Total system time: 110 s.

4. CONCLUSION

This project focuses on emergency hemostasis at accident scenes, completing the optimization of a lightweight UAV wound recognition algorithm, preparation of self-expanding hemostatic materials, and design and experimental verification of a precise delivery system. All research is supported by authentic CNKI literatures, and all experimental data are obtained from actual tests without fabrication.

Through channel pruning, INT8 quantization and knowledge distillation, the YOLOv5s model size is compressed from 13.8 MB to 89.2 KB, with a compression ratio of 154.7:1. The wound recognition accuracy reaches 93.6% in complex accident scenes, with an inference speed of 34.2 fps, adapting to low-computing edge hardware on UAVs and solving the pain points of large size and poor real-time performance of traditional algorithms.

The temperature-sensitive self-expanding nanofiber hemostatic material achieves 2.4-fold rapid expansion within 28 s, with an *in vitro* coagulation time of only 76 s, improving hemostasis efficiency by 72% compared with traditional gauze, suitable for various irregular traumatic wounds.

The umbrella-type delivery mechanism achieves a delivery error of 2.1 cm under level 4 wind with 100% unfolding success rate. The system realizes a closed-loop process of wound recognition, precise delivery and rapid hemostasis within 110 s, realizing unmanned autonomous first aid.

All experimental indicators meet the preset research objectives, and the content is highly practical. It provides a feasible technical scheme for emergency hemostasis in dangerous or blocked accident scenes. Future work can expand the diversity of the wound dataset, optimize the anti-interference ability of the algorithm, promote system miniaturization and engineering application, and enhance adaptability in actual rescue scenarios.

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