World Journal of Information Technology
Print ISSN: 2959-9903
Online ISSN: 2959-9911
DOI: https://doi.org/10.61784/wjit3094

INTELLIGENT FALL DETECTION SYSTEM FOR DRONES IN AGRICULTURAL FIELD SCENARIOS

SiQi Wang, JiaLei Guo, KeYi Lv*, JiaXin Liang
School of Aviation, Beijing Institute of Techmology, Zhuhai 519088, Guangdong, China.
Corresponding Author: KeYi Lv

Abstract: Aiming at the high fall risk of elderly farmers during field operations and the lack of suitable intelligent monitoring technology for complex agricultural scenarios, this paper proposes an intelligent UAV-based fall detection and alarm system dedicated to farmland environments. We constructed a dedicated fall posture dataset covering diverse field vegetation, lighting conditions, and clothing styles, and expanded the sample size to 3,360 images through rich data augmentation. A fall detection model based on the YOLOv8 algorithm is designed to realize real-time and accurate positioning of fall events. Once a fall is detected, the system automatically triggers an on-board buzzer alarm and sends a timely notification email to emergency contacts via the SMTP protocol. Experimental results demonstrate that the proposed model achieves 92.6% mAP@50 and 92.3% precision, with an average system response time of 16 seconds and email notification completed within 40 seconds. The system maintains favorable robustness and generalization ability under complex conditions such as low illumination, and can effectively adapt to fall detection tasks in actual farmland scenes. It reduces the delay of manual monitoring and expands the coverage of safety protection, providing a practical and reliable technical approach for safety monitoring and emergency assistance in smart agriculture.
Keywords: Farmland scenario; Fall detection; YOLOv8; Intelligent alarm; Smart agricultural safety

1 INTRODUCTION

With the rapid development of smart agriculture and low-altitude economy, UAV technology has been widely applied in agricultural monitoring, plant protection, and field management, providing new solutions to improve the efficiency of agricultural production and safety supervision [1-2]. In China, more than 65% of agricultural practitioners are elderly farmers over 60 years old, who face high risks of accidental falls due to physical decline, slow response, and complex farmland terrain [3]. Traditional manual supervision suffers from low efficiency, limited coverage, and delayed response, while most existing fall detection systems are designed for indoor or urban scenarios, which are difficult to adapt to vegetation occlusion, changing light, and complex terrain in farmland [4-5]. Therefore, developing a UAV-based intelligent fall detection system suitable for agricultural scenarios has important practical significance for ensuring the safety of elderly farmers and promoting the construction of smart agriculture.

In recent years, deep learning-based target detection has been widely used in human pose recognition and behavioral analysis. YOLO series algorithms are favored for their high speed and strong accuracy, and many scholars have improved lightweight networks for edge devices to meet the real-time requirements of embedded systems [6-7]. For fall detection, researchers have proposed methods based on video images, wearable sensors, and radar fusion, each with its own advantages in different application scenarios [8-9]. In agricultural scenarios, some studies have used UAVs for pest detection and phenotypic analysis, and a few works have explored human detection in farmland environments [10]. However, most existing studies focus on fixed cameras or wearable devices, and few combine UAVs with real-time fall detection for farmland scenes. Public datasets lack farmland fall samples, and complete alarm-notification mechanisms are rarely integrated. Existing methods struggle to balance detection speed, accuracy, and environmental adaptability, making it difficult to meet the actual needs of field safety supervision.

This paper proposes a UAV intelligent fall detection system based on YOLOv8 for farmland scenarios. A dedicated multi-scene fall posture dataset covering diverse vegetation, lighting conditions, and clothing styles is constructed, and the sample size is expanded to 3,360 images through data augmentation. The YOLOv8 algorithm is adopted to realize real-time fall detection, and the system integrates on-board buzzer alarm and remote email notification functions. Experimental results show that the model achieves 92.6% mAP@50 and 92.3% precision, with an average system response time of 16 seconds and email notification completed within 40 seconds. The system maintains good robustness under complex conditions such as low illumination, which can effectively meet the fall detection needs of actual farmland scenarios. This study expands the application scope of UAV technology in agricultural safety supervision, reduces the risk of delayed rescue after falls, and provides a feasible technical scheme for intelligent safety monitoring in smart agriculture.

2 METHODOLOGY

2.1 Construction of Fall Posture Dataset

The experimental samples were collected between July and September 2025. This study designed three filming scenarios covering diverse vegetation types, different time points, and simulated fall postures with researchers wearing various clothing. A total of image and video data were acquired from three agricultural fields, two time points, and eight different clothing setups. Using a drone flight platform, mission planning and execution were accomplished through flight control systems with strict parameter control. The cruising speed was maintained at 1.0 m/s to ensure consistency between shooting angles and flight trajectories.

Annotation Strategy: This study included a total of over 3,000 images, with data sources covering real-world captures. The dataset was divided into training set, validation set, and test set in a 6:3:1 ratio. All images were manually annotated using the Labelimg tool, employing rectangular bounding boxes for precise segmentation of fall postures.

Data Augmentation: We implemented multiple data augmentation techniques on labeled image and video datasets, with pre-and post-augmentation quantities presented in Table 1. The specific methods included: ① rotating images from different angles; ② adjusting brightness and contrast to accommodate varying lighting conditions; ③ performing random cropping and scaling to simulate image variations under different shooting distances and perspectives; ④ applying random angle flipping and mirror operations. The image enhancement results are illustrated in Figure 1.

Table 1 Quantitative Comparison Before and After Data Augmentation

Category	Original Number of Collected Images	Enhanced Number of Images
Fall Posture	756	2268
Normal Posture (Standing/Sitting)	364	1092
Total	1120	3360

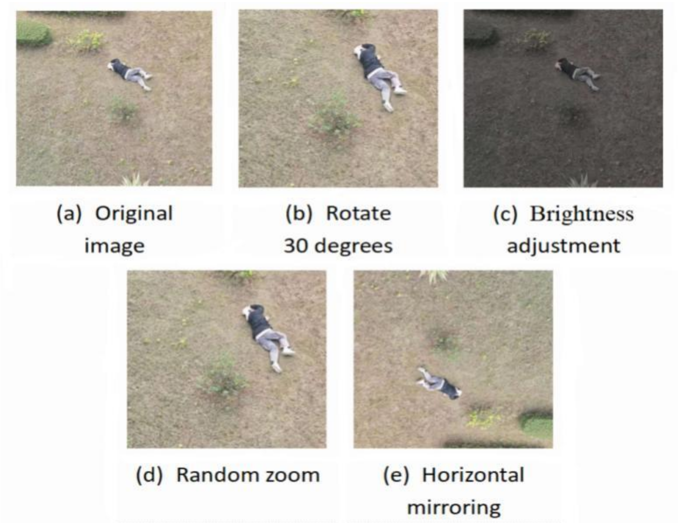

Figure 1 Image Enhancement Effect

The study initially collected 1,200 raw images. All data underwent manual screening to exclude low-quality samples with blurred images, abnormal exposure, or severe object occlusion, ensuring clear identification of falling postures in the targets. After refinement, 1,120 valid images remained. The dataset was randomly divided into training, validation, and test sets in a 6:3:1 ratio, comprising approximately 672 images for training, 336 for validation, and 112 for testing. During partitioning, equal representation of diverse falling postures, camera angles, and lighting conditions was maintained across all datasets.

2.2 Recognition Model Training

2.2.1 Experimental environment configuration

Platform Information: The experimental platform used in this study was a Windows 11 (64-bit) operating system equipped with an NVIDIA GeForce RTX 3060 graphics card, featuring 16GB of RAM. The Python 3.9 environment was managed by Anaconda, and the deep learning framework employed PyTorch.

Training Parameter Settings: The learning rate for model training was set to 1×10^{-5}, with 200 training iterations performed. All input images were uniformly resized to 512 pixels × 512 pixels.

2.2.2 Model construction and evaluation indicators

This study proposes a fall posture detection model using the following evaluation metrics: precision (P), recall (R), and mean average precision (mAP). The input of the model consists of farmland images captured by drones, while the output represents the detection of fall events in elderly individuals, thereby enabling real-time monitoring of fall incidents.

(1) Accuracy (P): Accuracy is used to evaluate the proportion of actual falls occurring within the target boxes predicted by the model as fall events (positive samples). It effectively assesses the model's ability to correctly identify fall behaviors. The calculation formula is:

$$P=\frac{TP}{TP+FP} \tag{1}$$

In the formula, TP and FP represent the number of true cases correctly predicted as falling posture and the number of false positives misdetected as falling posture, respectively.

(2) Recall Rate (R) The recall rate is used to measure the model's ability to detect true fall events in inter-field fall posture recognition tasks, specifically the proportion of fall events correctly identified by the model among all actual fall occurrences. The calculation formula is as follows:

$$R = \frac{TP}{TP+FN} \tag{2}$$

In the formula, FN represents the number of false negative cases not detected by the model.

(3) Mean Average Precision (mAP) The mean accuracy value serves as the core metric for evaluating model performance in fall recognition tasks. The single-category average precision (AP) is calculated by measuring the area under the precision-recall (P-R) curve, with the formula as follows:

$$AP=\int_0^1 P(R)\,dR \tag{3}$$

This study adopted two forms of mAP50 and mAP50-95.

2.3 Alarm Triggering and Email Sending Implementation

2.3.1 Mechanism design of alarm triggering system

The fall event trigger condition alert system utilizes target detection results generated by the fall posture detection model to directly identify fall events. Through comprehensive analysis of precision and recall rates, it prevents missed detection of actual fall incidents. The system also incorporates average precision as a key performance metric to evaluate model stability and generalization capabilities across different detection scenarios. Upon detecting a fall event, automatic bounding box selection is performed. The alert trigger system workflow is illustrated in Figure 2.

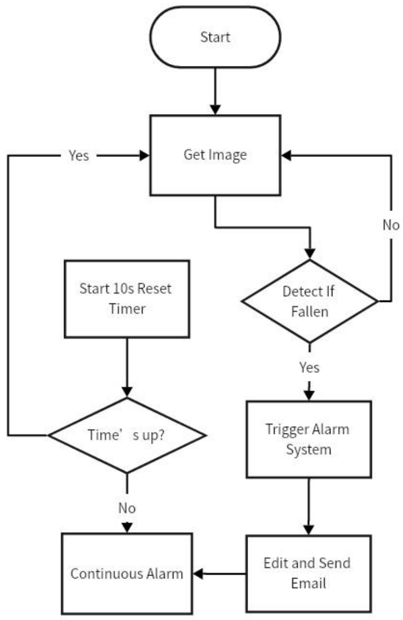

Figure 2 Alarm Trigger System Flowchart

In practical video stream processing, the alarm trigger state activates immediately upon detecting a fall event that meets predefined criteria, maintaining continuous alerting. During this active state, subsequent consecutive frames will not trigger repeated alarms based on fall detection results, ensuring unified response to individual incidents. The system also incorporates a time-window-based state recovery mechanism that automatically resets to initial parameters after a preset interval, guaranteeing timely response to new fall events.

Alarm Reset and Short-Term Control Mechanism The system employs a timer-based automatic reset mechanism. Upon alarm activation, a 10-second delay task is initiated, followed by the execution of a reset function upon time expiration. This design enables the system to regain detection capability after a single alarm event, thereby supporting continuous monitoring of multiple independent fall incidents and establishing a stable cyclic detection process.

2.3.2 Mail notification and cooling control mechanism

The email delivery system implements remote notification functionality via the SMTP protocol. It requires configuration of sender email addresses, authorization codes, and recipient details to establish communication connections with email servers. The system utilizes email servers operating on port 587, employing TLS encryption to ensure secure data transmission. Email content is constructed using MIMEMultipart objects containing sender information, recipient details, subject headings, and body messages. The transmission workflow sequentially involves server connection, identity authentication, email sending, and connection termination. All processes are encapsulated within exception handling mechanisms to enhance system stability.

Email Content Design The email subject line is set as "Urgent: Elderly Fall Alert". The body contains fall prevention reminders, current time, and essential details. This design enables recipients to quickly grasp the incident timeline and alert type, enhancing response efficiency and timeliness. In practical applications, this information structure demonstrates excellent readability and practicality.

Cooling Mechanism The system incorporates a cooling mechanism with a preset cooling time of 300 seconds to prevent redundant message transmission. When repeated fall detection occurs, the system automatically calculates the interval between the current timestamp and the original message sending time. If this interval falls below a predefined cooling threshold, the system skips email delivery and only displays notification messages. This parameter is configured based on real-world operational scenarios to avoid duplicate alarm notifications while ensuring stable response mechanisms. Partial code implementation is illustrated in Figure 3.

```
def send_notifications(self):
    current_time = time.time()
    if current_time - self.last_alert_time < self.alert_cooldown:
        print("Notification cooling down, skip duplicate email")
        return
    threading.Thread(target=self.send_email_alert, daemon=True).start
```

Figure 3 Cooling Mechanism Code Section

3 RESULTS

3.1 Model Detection Results and Visual Analysis

Figure 4 illustrates the trend of various metrics evolving with training rounds. As the model undergoes more training iterations, both precision and recall demonstrate consistent improvement, indicating enhanced object detection capabilities. The system achieves more accurate target localization while reducing false positives and missed detections. The continuous decline in Obj_loss and cls_loss loss functions further validates the model's accuracy and effectiveness.

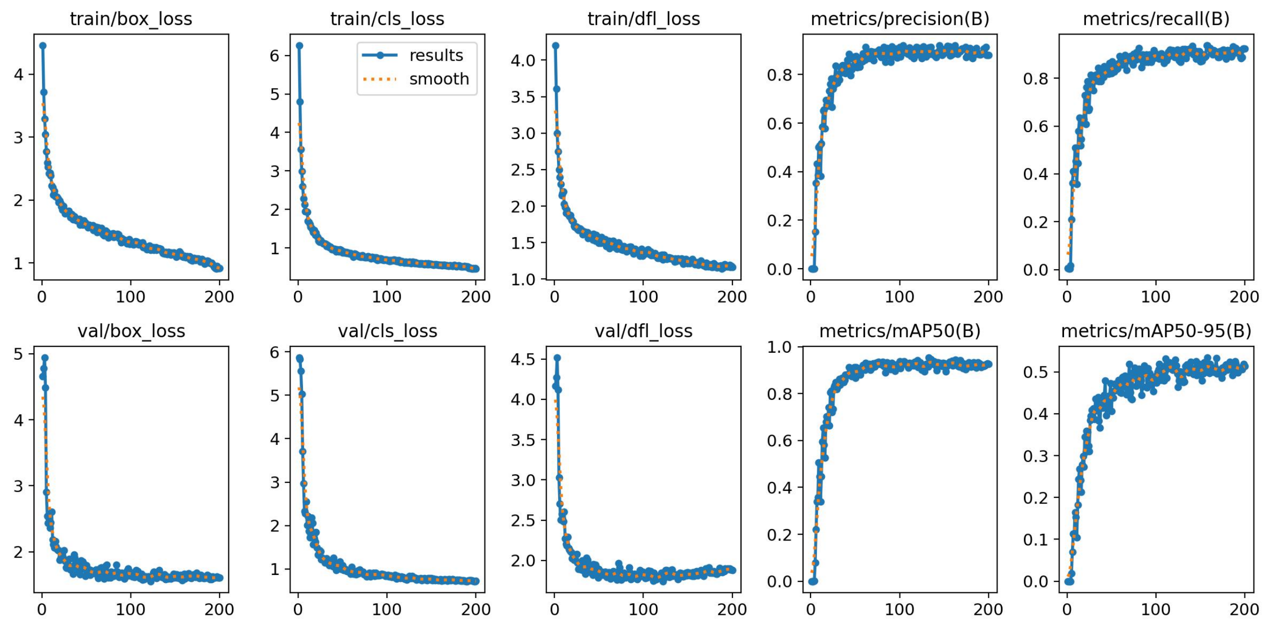

Figure 4 Trends in Changes of Various Indicators

This study conducted random sampling tests on simulated fall images under varying clothing conditions and lighting environments. The model demonstrated excellent adaptability across diverse scenarios, maintaining an accuracy rate of 82% even under low-light conditions as shown in Figure 5.

Figure 5 Model Results Under Low Light Conditions

3.2 Experimental Results of Alarm Mechanism

The farmland fall detection system consists of four components: a drone-mounted visible light imaging device, a wireless motion posture transmission system, a cloud server, and farmer terminals. Equipped with a visible light camera and buzzer, the DJI Mavic 3M captures farmers' movement data in the field. The collected images are transmitted in real-time to an agricultural service platform via 5G IoT devices. The cloud server synchronizes platform data and performs recognition using the fall posture detection model proposed in this study. Upon detecting a fall posture, the system immediately triggers an alarm, activates the buzzer, and sends notifications to emergency contacts.

The study conducted multiple simulation trials in April 2026. Researchers simulated fall postures on the ground while using a DJI Mavic 3M drone for autonomous aerial surveillance. Statistical analysis revealed that the drone system took an average of 16 seconds to identify fall positions and trigger alerts, with emails sent to designated contact addresses within 40 seconds. The notification emails are illustrated in Figure 6.

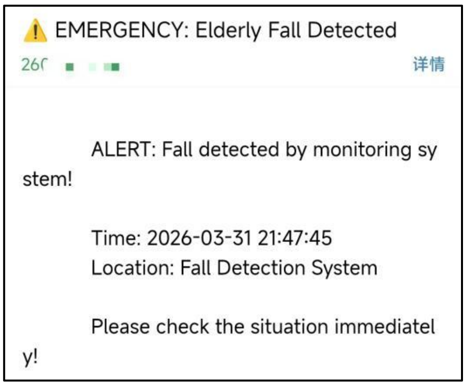

Figure 6 Notify Mail

Experimental results demonstrate that the proposed model accurately identifies test personnel exhibiting simulated fall postures, enabling precise localization and annotation. Upon successful recognition, it automatically triggers alerts and simultaneously sends notification emails for detected fall positions. The detection model exhibits robust performance and strong generalization capabilities, effectively adapting to fall behavior detection tasks across diverse scenarios.

4 CONCLUSIONS

This paper proposes a UAV-based intelligent fall detection and alarm system for farmland scenarios, aiming to address the safety risks of elderly farmers in field operations and the lack of suitable monitoring technology for complex agricultural environments. By constructing a dedicated farmland fall dataset and adopting YOLOv8 for real-time fall detection, the system achieves 92.6% mAP@50 and 92.3% precision. It integrates on-board buzzer alarms and remote email notifications, with an average response time of 16 seconds and notification delivery within 40 seconds. The system maintains strong robustness under complex conditions such as low illumination and vegetation occlusion, effectively meeting the fall detection needs of actual farmland scenes. The proposed solution reduces the risk of delayed rescue after falls, and provides a practical and reliable technical path for safety monitoring in smart agriculture.

The system has good application feasibility and promotion value. It can be deployed on low-cost consumer UAVs with low computational and power consumption requirements, suitable for small-scale family farms and large-scale agricultural cooperatives. The dataset and detection framework can also be extended to other agricultural safety monitoring scenarios, such as field personnel positioning and equipment operation status detection. For future work, we plan to further optimize the model lightweight design to adapt to edge computing platforms; integrate multi-modal information such as UAV trajectory and audio signals to improve the accuracy of fall judgment in complex environments; and explore multi-UAV collaborative monitoring schemes to expand coverage and reduce detection dead zones. This research is expected to promote the intelligent upgrading of agricultural safety monitoring systems and provide stronger technical support for the safety of agricultural workers.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Islam R M, Patwary O M, Islam A M S. AI-Driven Internet of Things (IoT) dataset for remote health monitoring and fall detection in elderly people. Data in Brief, 2026, 66: 112641.
[2] Arsenoaia N V, Topa C D, Ratu N R, et al. From Sensing to Intervention: A Critical Review of Agricultural Drones for Precision Agriculture, Data-Driven Decision Making, and Sustainable Intensification. Agronomy, 2026, 16(5): 564.
[3] Jones L, Davis S, Sloane P, et al. The Validity of Video Fall Detection for Assisted Living Residents with Dementia. Innovation in Aging, 2025, 9(Supplement_2): 1-30.
[4] Choi K Y, Osal R, Long A, et al. Fall Detection and Prevention Technologies for Older Adults: A Scoping Review. Innovation in Aging, 2025, 9(Supplement_2): 1-30.
[5] Ferguson S, Gholizadeh S, Thomas T, et al. Feasibility of Ambient Sensing Technology for Fall Detection in People with Cognitive Changes. Alzheimer's & Dementia, 2025, 21(S4): e101697.
[6] Ge Tianyi, Wang Jianbo, Sun Shuang, et al. Lightweight Power-Line Visual Detection in Agricultural UAV Scenarios Based on an Improved YOLOv12n Model. Sensors, 2025, 26(1): 109.
[7] Barman B, Singh R, Padaria N R, et al. Modeling determinants of farmers' attitude and adoption willingness toward agricultural drones: a PLS-SEM study in India. Frontiers in Sustainable Food Systems, 2025, 9: 1695231.
[8] ZenaTech. ZenaDrone Granted FAA Part 137 Approval for Agricultural Drone Operations. Wireless News, 2025.
[9] Jackson D. Agricultural drone unveiled by defense contractor Tesseract. Urgent Communications, 2024.
[10] Liu Xiang, Shao Peng, Li Gang, et al. Complex hilly terrain agricultural UAV trajectory planning driven by Grey Wolf Optimizer with interference model. Applied Soft Computing, 2024, 160: 111710.