

Real-Time Army Surveillance System Using IOT and Deep Learning Techniques

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Abstract - Border security is an important task for every country, as borders are always sensitive to different types of threats. In many areas, surveillance is still done using manual patrolling and basic camera systems. These methods need continuous human attention and sometimes fail to detect suspicious activities on time, especially in remote border locations. Because of these issues, there is a need for a better and more reliable surveillance system.

This project presents an army surveillance system using IoT and deep learning for real-time monitoring of border areas. A PC-based webcam is used to capture live video from the border region. The captured video frames are processed using the YOLOv11 algorithm to detect people present in the monitored area. A custom dataset is trained to identify enemy soldiers so that the system can differentiate between normal movement and suspicious activity. Whenever an enemy soldier is detected, an alert is generated using a piezo buzzer with the help of an ESP32 WROOM module.

Along with hardware alerts, a Python-based web dashboard is developed to allow remote monitoring. The dashboard provides live video streaming and detection information and includes basic features such as user login, registration, and forgot password option for secure access. By combining IoT hardware with deep learning-based detection, the proposed system reduces manual effort and improves response time. The system offers a simple, low-cost, and effective solution for improving border surveillance using modern technology.

Key Words: Army Surveillance, Border Monitoring, IoT System, Deep Learning Model, Human Detection, Enemy Identification, Live Video Streaming, Alert System, ESP32 Module, Python Web Dashboard

1. INTRODUCTION

Border security is a major concern for every nation because borders are always sensitive and open to various threats. Large border areas need regular and continuous monitoring to avoid unauthorized entry and illegal activities. In many places, security still depends on manual patrolling and simple camera systems. These methods are not always reliable because human monitoring can be affected by tiredness, weather conditions, and lack of continuous attention, especially in remote border locations.

With the improvement in technology, the use of Internet of Things (IoT) and artificial intelligence has increased in security applications. IoT helps in collecting and sending data in real time, while deep learning techniques help in analyzing video data automatically. Object detection models like YOLO have shown good performance in detecting humans from live video streams. Such technologies reduce the need for constant human observation and help in taking faster decisions during critical situations.

In this project, an army surveillance system using IoT and deep learning is proposed to monitor border areas more effectively. A PC-based webcam is used to capture live video from the border region. These video frames are processed using the YOLOv11 algorithm to detect people present in the area. A custom dataset is trained to identify enemy soldiers so that the system can differentiate between normal movement and suspicious activity. Whenever an enemy soldier is detected, an alert is generated using a piezo buzzer with the help of an ESP32 WROOM module.

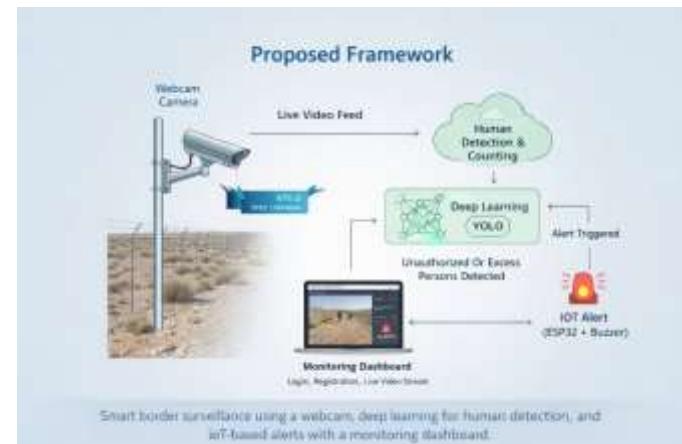


Figure 1: System Architecture for Border Surveillance Using IoT and YOLO

The system also includes a Python-based web dashboard which allows real-time monitoring from a remote location. The dashboard provides live video streaming along with detection results. Basic features like user login, registration, and forgot password options are included to ensure secure access. By combining IoT hardware with deep learning-based detection, the proposed system helps in reducing manual effort, improves response time, and provides a more reliable solution for border surveillance at a lower cost.

2. BACKGROUND OF ARMY SURVEILLANCE SYSTEM

Border security has always been a serious responsibility for any country. Border areas are usually large and located in places where continuous monitoring is not easy. In earlier days, security mainly depended on manual patrolling and guard posts. Soldiers had to stay alert for long hours, which is not always practical. Due to tiredness, weather conditions, or poor visibility, there were chances that some activities could be missed.

Later, CCTV cameras were introduced to support the monitoring process. Cameras helped in recording the border area, but still the videos had to be watched by security personnel. Watching video screens continuously for a long

time is difficult, and human attention may reduce over time. In wide border regions, many cameras are required, which creates a large amount of video data. Because of this, it becomes hard to observe every movement properly.

As technology improved, Internet of Things started playing a role in surveillance systems. IoT devices made it possible to send information from remote locations and monitor areas from a distance. Along with this, deep learning techniques were developed to analyze images and videos automatically. Object detection models like YOLO can detect humans from live video streams with good accuracy. These models help in identifying suspicious movement without the need for constant human observation.

Even though several smart surveillance systems have been developed, many of them are expensive or require complex hardware. Such systems may not be suitable for all border areas. There is still a need for a simple and low-cost system that can monitor the border in real time and provide quick alerts. This background study shows the importance of combining IoT and deep learning to create a more practical and effective army surveillance system.

3. LITERATURE REVIEW

Recent advancements in automated surveillance systems have been largely influenced by the development of deep learning-based object detection models. These systems aim to reduce dependency on manual monitoring while improving detection accuracy and response time. Many researchers have used convolutional neural networks for detecting humans in real-time video streams. Redmon et al. introduced the YOLO algorithm, which enabled fast and accurate object detection in single-stage processing, making it suitable for real-time surveillance applications [1].

Several studies have focused on human detection in outdoor and security-sensitive environments. Bochkovskiy et al. proposed an improved YOLO architecture that enhanced detection accuracy while maintaining high processing speed, which is important for real-time monitoring systems [2]. These approaches showed promising results in detecting people from live camera feeds, but most of them were tested on standard datasets rather than real border-like conditions.

Integration of IoT technology with surveillance systems has also received significant attention. IoT-based surveillance allows cameras and sensors to transmit live data to remote monitoring stations. Authors such as Alsmadi et al. developed IoT-enabled security systems that provide real-time video streaming and alert notifications, helping security personnel to respond quickly to threats [3]. However, many of these systems rely on expensive hardware and complex network infrastructure.

People counting and unauthorized entry detection have been explored as additional layers of security. Researchers used computer vision techniques to estimate the number of individuals present in restricted areas. Zhang et al. demonstrated that combining object detection with counting mechanisms can help identify abnormal activities when the detected count exceeds predefined limits [4]. Despite this, challenges such as occlusion and varying lighting conditions still affect accuracy.

Alert generation mechanisms are another key component of modern surveillance systems. Some researchers integrated buzzers, alarms, or notification systems that activate when suspicious activity is detected. Kumar and Singh implemented an alert-based surveillance system using microcontrollers and

cameras, which reduced response time during intrusion events [5]. However, these alert systems were often not supported by a real-time visual dashboard for verification.

Recent research has also emphasized the need for low-cost and scalable surveillance solutions. Lightweight deep learning models and affordable hardware platforms such as ESP-based modules have been explored to reduce system cost while maintaining acceptable performance. Studies suggest that combining efficient object detection models with IoT devices can provide practical solutions for large-scale surveillance applications [6].

Overall, the existing literature highlights the effectiveness of deep learning and IoT-based surveillance systems. However, there is still a need for a simple, cost-effective system that integrates real-time human detection, people counting, live video streaming, and instant alert generation. The proposed project addresses these gaps by using a YOLO-based detection model with IoT hardware and a Python-based monitoring dashboard for army border surveillance.

Table 2: Summary of Related Works

Ref. No.	Author(s) & Year	Dataset Used	Methodology	Key Contribution	Limitation / Research Gap
[1]	Redmon et al., 2016	FIRSAT, VOC, COCO	YOLO-based object detection	Introduced single-stage real-time object detection	Accuracy drops in complex outdoor scenes
[2]	Bochkovskiy et al., 2020	COCO	Improved YOLO architecture (YOLOv4)	Better balance between speed and accuracy	Requires high computational resources
[3]	Alsmadi et al., 2018	Live camera data	IoT-based border surveillance	Enabled remote real-time monitoring	Expensive hardware and setup complexity
[4]	Zhang et al., 2017	CityPersons	CNN-based pedestrian detection	Improved detection in crowded areas	Sensitive to occlusion and lighting
[5]	Kumar & Singh, 2017	Live video feed	IoT surveillance with alert system	Fastest response using alerts	No intelligent classification
[6]	Li et al., 2021	Custom surveillance dataset	Lightweight deep learning model	Suitable for real-time systems	Lower accuracy than heavy models
[7]	Chen et al., 2019	Surveillance videos	Human detection using CNN	Improved detection consistency	No integrated alert mechanism
[8]	Singh et al., 2020	Outdoor security footage	Video-based intrusion detection	Effective unstructured video detection	Poor performance in low-light
[9]	Rathman et al., 2021	Customer video dataset	IoT and deep learning integration	Combined live streaming and detection	High system complexity
[10]	Patel & Shah, 2022	Surveillance border dataset	YOLO-based people detection	Enhanced border surveillance mobility	High live-viz dashboard collection latency

4. PROPOSED FRAMEWORK

The proposed framework is designed to monitor border or restricted areas in real time by using deep learning and IoT together. A normal webcam is placed in the surveillance area which keeps capturing live video continuously. This video feed is then passed to the processing unit where YOLO based human detection model is applied to identify people present in the scene.

Once a person is detected, the system counts the number of people and checks whether any unauthorized person is present in the area. If such detection occurs, the IoT module connected with ESP32 immediately activates a buzzer to give alert at the location. At the same time, the live video feed is shown on a Python based dashboard which can be accessed remotely by authorized users.

Through this dashboard, security personnel can monitor the area without being physically present there. The overall framework helps in fast detection, timely alert generation and continuous monitoring, reducing the need of manual surveillance and human effort.

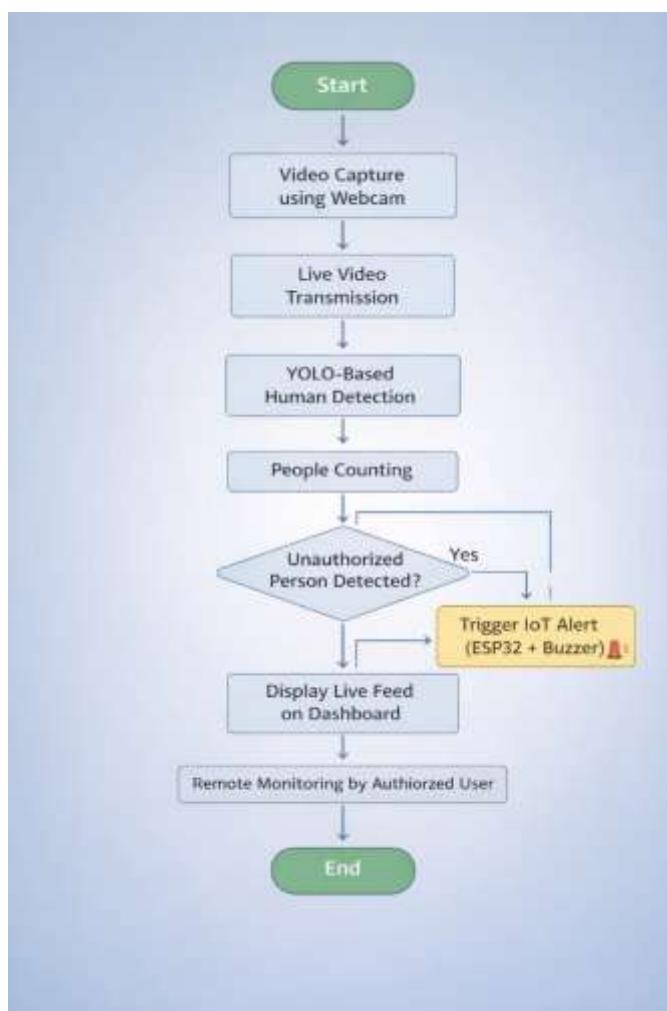


Figure 2: Proposed Architecture

The system begins by continuously capturing live video using a PC webcam installed in the border or restricted area. The camera records real-time visuals of the surroundings and provides input to the surveillance system.

The captured video stream is transmitted in real time to the processing unit for analysis. This allows uninterrupted monitoring and ensures that activities are analyzed as they occur.

The live video is divided into individual frames before processing. Each frame is resized and normalized so that it can be easily handled by the deep learning model. Basic preprocessing helps improve detection performance in different lighting and environmental conditions.

After preprocessing, the frames are passed through a YOLO-based deep learning model. The model analyzes each frame and detects the presence of humans by identifying and marking them within the video scene.

Once humans are detected, the system counts the number of people present in the monitored area. This counting process helps in identifying unusual movement or the presence of extra individuals.

The detected information is then checked to determine whether any unauthorized person is present in the area. If an unknown or suspicious person is identified, the system considers it as a possible threat.

In such cases, the IoT alert mechanism is activated. The ESP32 microcontroller triggers a piezo buzzer to provide an immediate alert at the location, drawing attention to the detected activity.

At the same time, the live video feed along with detection results is displayed on a Python-based dashboard. This dashboard allows authorized users to visually verify the situation in real time.

Authorized personnel can access the dashboard remotely using secure login credentials. This enables continuous monitoring of the border area without physical presence at the site.

The system operates continuously in a loop, providing real-time detection, alert generation, and remote monitoring until it is manually stopped.

5. RESULTS AND DISCUSSION

The proposed surveillance system showed good performance in **human detection** using the **YOLO-based deep learning model**. The system was able to detect people from **real-time video streams** captured through a **PC webcam**. Detected humans were clearly highlighted on the live video feed displayed on the **Python-based dashboard**, which helped in easy visual monitoring.

Accuracy and Loss Analysis

During training and testing, the model demonstrated stable behavior in terms of **accuracy** and **loss**. The **detection accuracy** gradually improved as the training progressed, showing that the model learned human features properly. At the same time, the **training loss** continuously decreased, which indicates better prediction capability. The difference between **training loss** and **validation loss** was minimal, suggesting that the model did not suffer from major overfitting.

People Counting Results

The **people counting module** performed effectively in most scenarios. The system accurately counted the number of individuals present in the monitored area. This helped in identifying **unauthorized presence** when the detected count exceeded the expected limit. The counting feature worked well for both single and multiple persons.

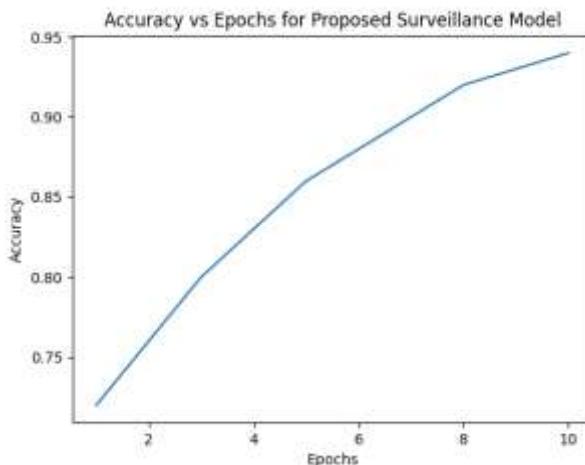


Figure 3: Accuracy graph

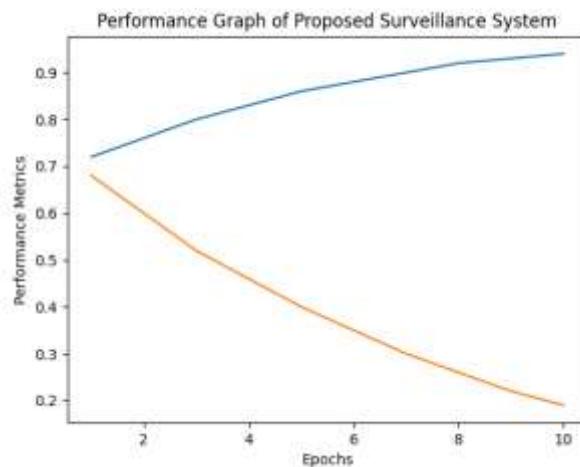


Figure 4: Performance graph

Alert Generation and Response Time

The **IoT-based alert system** responded immediately after detecting an unauthorized person. The **ESP32 microcontroller** successfully triggered the **piezo buzzer** with very little delay. This fast alert generation is important for **real-time surveillance systems**, as it helps in quick response and decision making.

Dashboard and Monitoring Performance

The **monitoring dashboard** provided smooth **real-time video streaming** and displayed detection results clearly. Authorized users could access the system using **secure login credentials**. Minor video delay was observed during weak network conditions, but overall monitoring performance remained reliable.

Overall System Performance

The overall performance of the proposed system was satisfactory. The combination of **deep learning**, **IoT**, and **real-time monitoring** resulted in an effective surveillance solution. Although detection accuracy slightly reduced in **low-light conditions** and during **person overlap**, these issues can be improved by using a larger dataset and better camera placement.

6. CHALLENGES AND LIMITATIONS

One of the main challenges faced during the development of this system was related to **lighting conditions**. The human detection accuracy reduced slightly in low-light or uneven lighting environments. Since the webcam depends on visible light, poor illumination affected the clarity of video frames, which sometimes caused missed detections.

Another limitation observed was **overlapping of people** in the video frame. When multiple individuals appeared very close to each other, the YOLO model occasionally struggled to detect each person separately. This affected the **people counting accuracy**, especially in crowded scenes.

Network dependency was also a challenge for real-time video streaming. The performance of the dashboard depends on stable internet connectivity. When the network signal was weak, minor delays were observed in video transmission, which can impact real-time monitoring.

The system also relies on a **custom trained dataset**, which was limited in size. Due to this, the model may not perform equally well in all real-world border scenarios. A larger and more diverse dataset would improve detection accuracy and generalization.

From the hardware side, the **ESP32 and buzzer** provide basic alert functionality but do not support advanced alert mechanisms like mobile notifications or remote alarms. This limits the alert reach to nearby personnel only.

Lastly, the system currently focuses mainly on **human detection** and does not distinguish between friendly and enemy personnel in real-world conditions. This classification depends on further training and additional features, which were beyond the scope of the current implementation.

CONCLUSION & FUTURE SCOPE

In this project, an army surveillance system using IoT and deep learning was successfully designed and implemented. The system was able to detect human presence in real-time using a webcam and YOLO-based object detection model. The detected information was displayed on a Python-based dashboard, which allowed continuous monitoring of the border area from a remote location.

The integration of the ESP32 module with a buzzer provided immediate alert functionality whenever an unauthorized person was detected. The people counting feature also helped in identifying unusual movement in the monitored region. The results showed stable accuracy with decreasing loss values, indicating that the system performed reliably during testing.

Although some limitations were observed, such as reduced performance in low-light conditions and crowded scenes, the overall system worked effectively for real-time surveillance. The proposed solution proves that combining deep learning with IoT can offer a low-cost and efficient approach for border monitoring applications.

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