

AN Analysis And Implementation Of Human Detection In Forest Easy Classification Using Machine Learning And IOT

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Abstract: - Human detection is a key part of computer vision systems. These systems are used in many fields, including surveillance, traffic monitoring, healthcare assistance, and human-computer interaction. Traditional machine learning methods, such as Haar-like features with cascaded classifiers and HOG-SVM approaches, depend on handcrafted features. They often struggle in situations with occlusion, complex backgrounds, or changing light. Recent developments in deep learning, especially Convolutional Neural Networks (CNNs), offer better solutions by learning features directly from raw images. In this study, we implement an efficient deep learning method for human detection using the MobileNet Single Shot Detector (MobileNet-SSD) with the OpenCV Deep Neural Network (DNN) module. MobileNet uses depth wise separable convolutions to greatly reduce computational needs. The SSD framework allows for object classification and localization at the same time in one forward pass. Our method processes real-time video streams and achieves strong detection accuracy while keeping frame rates suitable for real-time applications, even on standard CPUs.

I. INTRODUCTION: - Human detection is a key issue in computer vision and an important part of many real-world applications. It is crucial for video surveillance, selfdriving cars, healthcare monitoring, and human-computer interaction. Accurately detecting and locating humans in images or video streams is increasingly important. The challenge is to achieve reliable detection under different conditions like changes in light, obstructions, variations in posture, and complex backgrounds. Traditional machine learning methods, such as Haar cascades and Histogram of Oriented Gradients (HOG) used with Support Vector Machines (SVM), have been commonly employed for human detection. While these methods are efficient, they depend on manually created features and struggle in complicated environments, which limits their scalability. The rise of deep learning, especially Convolutional Neural Networks (CNNs), has changed the field. Deep learning allows automatic feature extraction and provides top performance in object detection tasks. Among the different deep learning models, Single Shot Detector (SSD) is fast and accurate for object detection, while MobileNet offers a lightweight backbone that works well on devices with limited processing power. When combined, MobileNet and SSD create MobileNet-SSD, which balances speed and accuracy, the OpenCV Deep Neural Network (DNN) module for real-time human detection.

II. AIM AND OBJECTIVE:-

- *Aim:- To build a smart, low-power system that can quickly detect people or animals using a lightweight AI model, sound a local alarm, and send instant SMS alerts with location and even in remote areas.*

Goals:-

- Instantly Spot People and Animals, Anywhere, Anytime.
- Automatic Beep Alarm Alert People Nearby Instantly.
- Get SMS Alerts on Your Phone Even Without Internet.
- Works on Low Power in Remote Areas.
- Location Tracking with GPS.
- Cloud Storage for Backup.
- Recognize Harmless vs Dangerous Animals.
- Adjustable Sensitivity to Avoid False Alarms.

III. PROPOSED METHODOLOGY:

1. Detection Model:- The system plans to use MobileNet-SSD (or MobileNet-SSD V2) in conjunction with OpenCV for real-time detection of both humans and specific animals (dog, cat, cow, sheep, horse, bird). MobileNet-SSD is chosen because it is a lightweight model that can run efficiently on standard hardware.

2. Alert Triggering:- Immediately upon detection of a human or animal, the system will execute two types of alerts:

- *Local Alert :-* A continuous beep sound is triggered locally.
- *Remote Notification :-* An instant SMS (Short Message Service) is sent to registered mobile number(s) using the Twilio module.

3. Deployment Integration:- The proposed work includes integrating with IoT infrastructure (like low-power devices) for deployment in remote areas such as farms or forests, enabling field monitoring

4. Enhancements and Fail-Safes (Optional/Future Work):- The plan also includes several additions for a robust system:

- Adding

GPS tagging to alerts to provide the precise location of the event

- Enabling

cloud storage/logging of captured images/video and metadata.

- Implementing

fail-safe design with backup power and the ability to operate with intermittent connectivity, falling back to SMS if the internet fails.

- Allowing

configurable sensitivity, detection zones, and thresholds to minimize false positives.

Comparison with existing method

Feature /Aspect	Existing Methods	Your Proposed IDS System
Detection Model	Often use heavy models like YOLOv3 or SSD on high-end systems	Uses lightweight MobileNet- SSD for real-time detection on low-power devices
Hardware Requirement S	Requires GPU or powerful CPU setups	Runs efficiently on Raspberry Pi or ESP32-CAM
Alert Mechanism	Mostly passive logging or delayed alerts	Instant local beep + SMS alerts to registered users
Animal Detection	Primarily focused on human detection only	Detects selected animals (dog, cat, cow, sheep, horse, bird) along with humans
False Positive Handling	Basic filtering, often prone to misdetections	Multi-frame verification, configurable sensitivity, and detection zones

IV. ADVANTAGES:-

1. Enhanced Security and Safety

Identifies any unwarranted or unauthorized presence of a person within sensitive or restricted areas.

Serves in the prevention of crimes and recognition of potential intruders.

2. Real-Time Monitoring

Provides alerts instantaneously via alarms, alerts, or SMS to allow a quicker response.

Can be used for monitoring surveillance in public spaces, offices, residential areas, and areas of concern for industrial entities.

3. Automation & Less Human Work

Can replace continuous manual oversight from security

Provides labour and operational cost and human time and effort savings.

4. Utilization of It Can Bridge Many Uses

Can be useful in smart home spaces, traffic surveillance, lessening lost life, in crowd control situations, and in health care spaces (such as fall detectors for the elderly).

5. Accuracy and Understandable Efficiency

Within realism, state-of-the-art systems (AI, Deep Learning, IoT-based) are accurate enough to detect a human presence in a range of situations.

Provides home monitoring in semi-dark to dark situations when leveraging thermal or infrared cameras.

6. Decision-Making Improvement

Provides data for analytics to include aspects human movement patterns, crowd density, activity recognition etc.

Will help law enforcement, smart city planning, and resource allocation.

V. CONCLUSION :-

Human detection is essential in today's world, supporting everything from surveillance and crowd control to disaster response and smart security. While older techniques like HOG and SVM have mostly been replaced by deep learning models like YOLO and CNNs—thanks to their higher accuracy—real-world challenges still remain. In busy, fast-changing, or partially blocked environments, even the best systems can struggle. Real-

time processing and IoT have helped make these systems more responsive, but accuracy doesn't always mean reliability. Many models still falter under tricky lighting, cluttered backgrounds, or unusual human movements, largely due to limited and less diverse datasets. To truly advance, future systems need to be smarter, faster, and more adaptable to real-world conditions. Using multiple types of sensors—like combining video with thermal or motion data—could boost performance. Adding the ability to understand behaviour and recognize human activities would also open up more possibilities. Ultimately, better data and smarter design are key.

Future plan:-

1. Improve Detection Accuracy in Complex Environments.
2. Optimization for Edge Devices.
3. Multi-modal Human Detection.
4. Dataset Expansion and Domain Adaptation.
5. supporting everything from surveillance and crowd control.
6. monitoring surveillance in public spaces, offices, residential areas, and areas.

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