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Pinaka: AI Surveillance Drone

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Abstract: *Railway derailment accidents caused by unidentified objects on the track are a significant safety concern, leading to loss of lives, infrastructure damage, service disruption, and high economic and social impact. To address this issue, we propose a drone-based surveillance system designed to identify and report hazardous objects on railway tracks in real-time. This project integrates drone technology with advanced object detection systems to enhance safety and prevent accidents. The drone is equipped with a high-resolution camera and an object detection algorithm capable of identifying hazards such as gas tanks, stones, steel poles, and other foreign objects. Using computer vision and deep learning, the system is trained to recognize threats commonly linked to derailments. Upon detecting an object, the drone sends immediate alerts to the loco pilot, admin, or control center, providing real-time information about the object's nature and location. This enables quick responses, such as dispatching emergency services or security personnel for checks. At its current stage, the drone is manually operated, allowing human control over flight paths and surveillance. Future versions aim to incorporate autonomous flight, with the drone flying predefined routes and continuously scanning for hazards. This would overcome the limitations of ground-based systems by providing a broader view and access to remote areas. The key components of the system include drone hardware, a robust object detection model using machine learning, a communication module for real-time alerts, and an interface for monitoring and response. This proactive solution enhances safety, reduces accident-related delays, and supports efficient railway track maintenance, ensuring safer and more reliable railway travel*

Keywords: Railway Safety, Pinaka, AI Surveillance, Object Detection, YOLOv5, Deep Learning, Real-time Monitoring, Drones, Track Hazards, GPS Alerts, MySQL, 4G/5G, Autonomous Flight, Infrastructure Security, Predictive Maintenance, Aerial Inspection, Control Center Integration

I. INTRODUCTION

Railway derailment accidents caused by unidentified objects on tracks pose a significant safety risk, leading to potential loss of lives, damage to infrastructure, disruption of services, and considerable economic and social impacts. To mitigate these risks, we propose a drone-based surveillance system designed to identify and report hazardous objects on railway tracks in real-time. This project integrates advanced drone technology with object detection systems, aiming to enhance railway safety and prevent accidents.

The proposed system utilizes a high-resolution camera mounted on a drone, coupled with a powerful object detection algorithm, to recognize and classify potential hazards such as gas tanks, stones, steel poles, and other foreign objects. By leveraging computer vision techniques and deep learning, the system is trained to detect these objects with high accuracy. Upon detection, real-time alerts are sent to relevant authorities such as the loco pilot, admin, or control center, enabling swift actions to avert accidents. Currently, the system operates manually, with human control over the drone's flight paths and surveillance activities. However, future iterations envision autonomous operation, where the drone can patrol predefined routes along railway lines, continuously scanning for potential threats. This will significantly expand the system's coverage, especially in remote or hard-to-reach areas, providing a comprehensive surveillance solution.

Key components of the project include drone hardware, a robust machine learning-based object detection model, real-time communication modules, and an intuitive user interface for monitoring and responding to alerts. The system is

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designed not only to improve railway safety but also to streamline railway maintenance operations by minimizing accident-related disruptions. Overall, this drone-based object detection system presents a proactive solution to improving railway track safety, leveraging cutting-edge technology to prevent accidents caused by unnoticed hazards and ensuring safer, more efficient railway operations.

Object detection is a fundamental task in computer vision that involves identifying and locating objects within an image or video. Unlike image classification, which simply assigns a label to an entire image, object detection classifies and provides a bounding box for each object in an image, allowing the detection of multiple objects simultaneously. This technology has significant applications, from autonomous vehicles and surveillance to retail and healthcare, where it aids in identifying items, people, and even medical conditions. One of the most popular approaches to object detection is the YOLO (You Only Look Once) algorithm. YOLO, developed by Joseph Redmon and colleagues, is designed for real-time object detection and has significantly influenced the field. Unlike traditional object detection models that run classification and localization in separate stages, YOLO treats object detection as a single regression problem. It uses a single convolutional neural network (CNN) to simultaneously predict bounding boxes and class probabilities, making it faster and more efficient.

YOLO divides an image into a grid, where each cell is responsible for predicting objects that appear in that cell. For each cell, the algorithm predicts a fixed number of bounding boxes, as well as the confidence scores for these boxes and the probability of each class. The confidence score reflects the likelihood that the bounding box contains an object and its accuracy, while the class probability indicates the likelihood of each detected object's class. YOLO’s efficiency comes from processing the image in a single pass, enabling real-time object detection with high accuracy.

One of YOLO's strengths is its speed. Earlier object detection models like R-CNN and Fast R-CNN required multiple passes through a network, which was computationally expensive and slow. YOLO, however, combines localization and classification in one forward pass through a neural network, achieving speeds capable of processing up to 45 frames per second in its base model and up to 155 frames per second in its optimized versions like Tiny YOLO. This makes it suitable for applications requiring high-speed processing, such as autonomous driving or live video analysis. Over the years, YOLO has evolved with various versions, each improving upon its predecessors. YOLOv2 introduced batch normalization and anchor boxes, enhancing its accuracy and efficiency. YOLOv3 added support for multi-scale detection, allowing it to better detect small objects by using a feature pyramid network. YOLOv4 and YOLOv5 have further refined the architecture by integrating newer advancements like the Mish activation function and better backbone networks, increasing accuracy without sacrificing speed.

A key aspect of YOLO is its ability to balance precision and recall, known as the precision-recall tradeoff. High precision means fewer false positives, while high recall means fewer false negatives. YOLO’s configuration allows it to achieve a balance between detecting objects correctly without an excessive rate of missed detections. Additionally, YOLO is designed to handle complex backgrounds and occlusions, as it evaluates the entire image context rather than isolated regions, making it highly effective in diverse environments. In addition to its speed, YOLO is widely adaptable and can be trained on custom datasets to detect specific objects, making it ideal for specialized applications. In fields like security, drones can use YOLO to detect specific threats, while in agriculture, it can identify plant diseases by detecting unique features in leaves. Its versatility extends to facial recognition, wildlife monitoring, and retail analytics.

Despite its advantages, YOLO has some limitations, particularly when it comes to very small objects or densely packed objects within an image, as the grid-based approach may struggle with closely situated objects. However, ongoing advancements in the YOLO family address these challenges, with YOLOv7 and YOLOv8 introducing modifications to improve small-object detection.

In summary, YOLO has revolutionized object detection by making it fast, efficient, and highly adaptable to real-time applications. Its development continues to push the boundaries of what is possible in computer vision, making YOLO a cornerstone for real-time detection applications across numerous industries.

Some of the salient features of the system are:

1) Real-Time Detection: The system provides real-time alerts to authorities, enabling a rapid response to potential hazards on railway tracks.

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2) Enhanced Safety: By identifying objects like stones, gas tanks, or metal poles, the system helps prevent accidents, ensuring the safety of trains and passengers.
3) Broader Surveillance: Drones offer an aerial perspective, covering large and remote areas that are difficult for ground-based surveillance to access.
4) Cost-Efficient: Automated surveillance reduces the need for manual inspection, resulting in lower operational costs in the long run.
5) Customizable Alerts: The system allows customization of notifications, enabling efficient prioritization and response based on the detected threat level.
6) Improved Infrastructure Maintenance: By constantly monitoring railway tracks, the system aids in early detection of damage or obstructions, optimizing maintenance efforts.
7) Scalability: Future upgrades, such as autonomous drone patrols, can further enhance coverage and reduce human involvement.

II. ALGORITHM DETAILS

Pinaka leverages advanced deep learning algorithms for real-time object detection and classification. Each model has been chosen based on its performance in visual recognition tasks and ability to operate under real-time constraints in a drone-based environment.

1. YOLOv5 (You Only Look Once Version 5)

Overview:YOLOv5 is a state-of-the-art convolutional neural network used for real-time object detection. It processes entire images in a single forward pass and detects multiple objects with bounding boxes and class probabilities.
Architecture -
Backbone: Extracts image features using CSPDarknet
Neck: Combines feature maps at multiple scales using PANet
Head: Outputs bounding boxes, objectness score, and class predictions
Use in Pinaka: YOLOv5 is used to detect track obstructions like rocks, cylinders, or poles in real-time drone footage. Its speed and accuracy make it ideal for immediate hazard recognition while the drone is in motion.

III. RELATED WORK

In [1], This paper proposes an innovative surveillance system aimed at addressing the limitations of traditional CCTV surveillance. It introduces a quadcopter-based autonomous tracking and following system using image processing techniques, particularly the Probability Hypothesis Density (PHD) filtering with a Markov Chain Monte Carlo (MCMC) implementation. The system is designed to enhance public safety by utilizing drones integrated with existing surveillance infrastructure. It features advanced object tracking, human tracking, and secure path planning, with a focus on energy-efficient coverage and dynamic communication among a swarm of drones. The paper highlights potential applications in improving public monitoring and security, with significant implications for future crime prevention and public safety management
In [2], This paper presents the development of an autonomous unmanned aerial vehicle (UAV) aimed at defense applications such as machinery maintenance and surveillance in sensitive areas like the Line of Control (LOC) and war zones. The drone operates autonomously using a Pixhawk flight controller, following predetermined paths while conducting surveillance and detecting human activities with the help of a deep learning algorithm. The system employs a backup auxiliary drone that ejects and secures data in case of emergencies. Key features include the use of cloud-based image processing, an efficient object detection algorithm (YOLOv3), and wireless communication for updating defense machinery remotely. This innovative design enhances both security and operational efficiency for defense purposes.
In [3], This paper explores the emerging field of surveillance drone cloud systems, focusing on the integration of drone technology with cloud computing. It presents a detailed concept of the "Drone Cloud" and its infrastructure, discussing various models and applications for surveillance, such as data sharing, AI-based analysis, and real-time drone-human

interaction. The paper also highlights the role of AI in enhancing surveillance capabilities, including object detection, anomaly detection, and real-time alerts. Additionally, it addresses the challenges and future research directions for drone cloud surveillance, emphasizing the importance of standardized connectivity, advanced AI features, and efficient resource allocation for large-scale drone deployments.

In [4],This paper presents an automatic object detection and tracking method for intelligent video surveillance, featuring a cooperative mechanism between detection and tracking modules. The approach consists of three main components: a detection module that utilizes a mixed Gaussian background model combined with Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) to accurately identify moving objects; a tracking module that employs Kernel Correlation Filters (KCF) for data association and occlusion handling; and a decision-making module that assesses the outputs from both previous modules to ensure reliable results. Experimental evaluations demonstrate that this method achieves high real-time performance and robustness, making it suitable for long-duration surveillance tasks, while effectively addressing challenges such as object occlusion and scale variations.

In [5],This paper investigates dynamic object detection and tracking in video surveillance, emphasizing the significance of computer vision in interpreting visual data. It outlines a comprehensive framework that includes three core components: moving object detection, object tracking, and event recognition. The authors highlight the challenges of accurately detecting foreground objects from video sequences, which is crucial for effective surveillance applications. The proposed methodology employs filtering techniques and thresholding to enhance video quality and segmentation accuracy based on features such as size, color, shape, texture, and intensity. The study introduces two frameworks: the Threshold Filtered Video Object Detection and Tracking (TFVODT) and the Improved Threshold Filtered Video Object Detection and Tracking (ITFVODT), both designed to optimize object recognition and tracking performance. Results demonstrate that the frameworks significantly improve detection accuracy and processing speed, showcasing their potential for real-time surveillance systems. The paper concludes by discussing the advancements made in object tracking using deep learning techniques like YOLOv3, achieving high accuracy across various datasets and conditions.

In [6],This paper discusses the design, implementation, and testing of a quadcopter system equipped with an automatic landing system and object detection capabilities, utilizing IoT technology. The quadcopter, developed primarily for surveillance purposes, is controlled via Raspberry Pi and OpenCV, with the code written in Python. The drone features auto-landing capabilities triggered by low battery levels and can monitor areas remotely through an IoT-enabled system. The paper explores the mathematical modeling of the quadcopter based on Newton-Euler and Euler-Lagrange methods, as well as thrust and motion conditions such as hovering, rise, and yaw. Key components include brushless DC motors and a Pixhawk flight controller. The quadcopter is tested for real-time object detection and surveillance, with a flight duration of 26 minutes and a total weight of 1.334 kg.

In [7],The paper CNN-based Counterfeit Indian Currency Recognition Using Generative Adversarial Network introduces a novel approach that leverages a combination of convolutional neural networks (CNNs) and generative adversarial networks (GANs). In this method, a CNN is used to classify currency notes as genuine or counterfeit, while the GAN generates high-quality counterfeit images to train and improve the CNN's ability to detect fake notes. The GAN acts as a counterfeit note generator, creating realistic-looking fake currency that the CNN must learn to distinguish from authentic currency.This adversarial training process enhances the CNN’s performance, as it is constantly exposed to more sophisticated counterfeit examples generated by the GAN. The result is a highly robust detection system that can handle even the most convincing counterfeit notes. However, the complexity of this approach requires significant computational power and a large dataset to train both the CNN and GAN models effectively. Despite these challenges, the combination of CNNs and GANs represents a cutting-edge solution for counterfeit detection, offering high accuracy and adaptability in real-world applications.

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IV. SYSTEM DESIGN

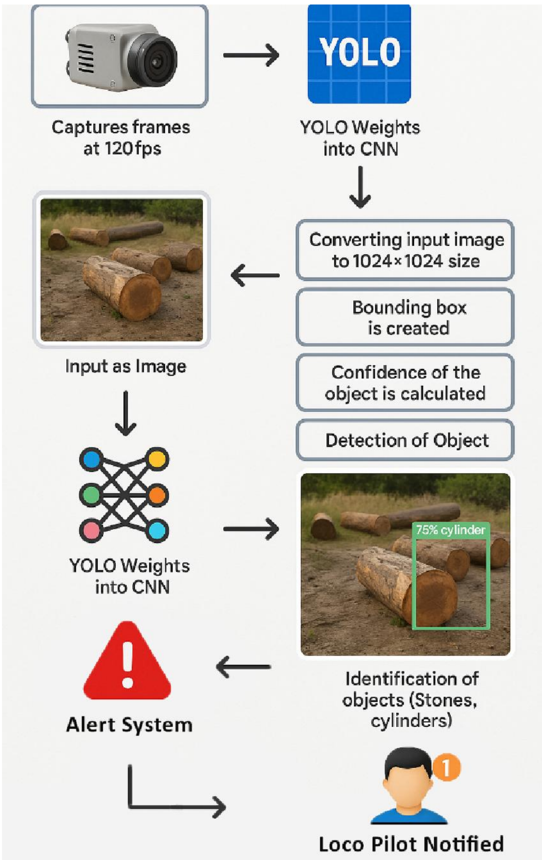

Fig. 1. System Architecture

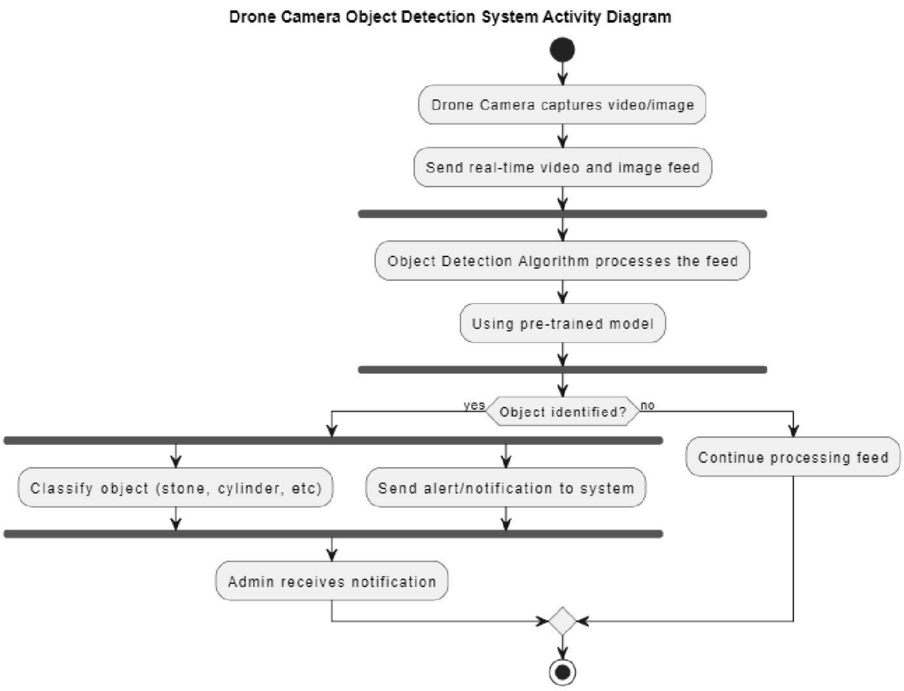

Fig. 2. Activity Diagram of the System

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The architecture of the proposed **Pinaka: AI Surveillance Drone** system consists of several core components: Pre-processing, Object Detection, Deep Learning Model, Alert System, and the Drone Hardware. Each of these elements plays a critical role in ensuring the efficient detection and reporting of hazards on railway tracks.

Pre-processing: The system begins with the drone capturing live video footage of railway tracks using its high-resolution camera. The video frames are pre-processed to enhance quality, including resizing, noise reduction, and contrast adjustment. This ensures the frames are standardized and ready for accurate object detection.

Object Detection: The pre-processed frames are fed into an advanced object detection module powered by deep learning. This module identifies potential hazards such as stones, gas tanks, steel poles, or other objects that may pose a threat to railway safety. The detection process involves identifying bounding boxes and labels for these objects in real-time.

Deep Learning Model: The core of the system is a custom-trained deep learning model designed for high accuracy and efficiency in object detection. The model utilizes a combination of convolutional neural networks (CNNs) and advanced algorithms to classify objects and filter out non-threatening items. It has been trained on a curated dataset of railway hazards for optimal performance.

Alert System: Once a hazard is detected, the system triggers an immediate alert. This alert is sent to the control center, loco pilot, or admin, providing details about the detected object's type and location. The system ensures timely action, such as deploying security personnel or emergency services.

Drone Hardware: The drone is equipped with a sturdy frame, a high-resolution camera, and a reliable communication module. These components enable the drone to operate effectively over vast railway stretches, capturing clear visuals and maintaining a seamless connection with the monitoring system.

User Interface: The admin or control center monitors the system through an intuitive interface. This interface displays real-time detections, alerts, and the drone's status. It provides actionable insights to ensure rapid decision-making and response to hazards.

This integrated architecture ensures that **Pinaka** can proactively detect and report threats, significantly enhancing railway safety and operational efficiency.

V. METHODOLOGY

A. Preparation of Dataset

The first step in the development of Pinaka: AI Surveillance Drone involves the preparation of a dataset. This dataset includes annotated images of various hazards that could appear on railway tracks, such as stones, gas tanks, steel poles, and other objects. The dataset is curated to represent a wide variety of scenarios, lighting conditions, and object orientations, ensuring robust training of the detection model.

B. Image Acquisition

Next, the drone acquires images of railway tracks using its high-resolution onboard camera. The live video feed is segmented into frames, which are then processed individually. The camera ensures that the captured frames have proper resolution, brightness, and clarity to maximize detection accuracy. Blurred or low-quality images could hinder the system's performance, so image quality is a critical factor.

C. Pre-processing

The acquired frames undergo a pre-processing phase to enhance their quality. This involves resizing the images to a standard dimension to simplify computations and applying noise-reduction techniques like Gaussian Blurring to remove unwanted artifacts. This step ensures that the images are uniform and ready for feature extraction and detection.

D. Gray- scale conversion

For computational efficiency, the pre-processed images are converted into grayscale. This reduces the image's complexity by eliminating color channels, allowing the system to focus on intensity variations. The simplified image structure improves the accuracy and speed of edge detection and object recognition.

E. Object Detection

Feature Detection using Deep Learning:

The processed grayscale images are passed through a deep learning-based object detection algorithm. The algorithm is trained on the prepared dataset to detect hazards. Using bounding boxes, the system identifies and highlights the location of each detected object, such as stones or gas tanks, in the image. This process is applied frame by frame, ensuring continuous detection in real-time.

Feature Extraction:

The detected objects' specific features, such as shape and size, are extracted for analysis. These extracted features are compared against stored features in the dataset to confirm the type of hazard.

Feature Comparison and Classification:

The extracted features are analyzed using advanced similarity metrics. The system determines the degree of match between the detected object and the known hazards in the dataset. This classification step ensures that only relevant threats are flagged.

VI. FUTURE SCOPE

While Pinaka currently focuses on real-time railway track monitoring using drone-based surveillance and AI-powered object detection, its underlying architecture offers significant potential for future expansion and enhancements. The following areas represent key directions for scaling the system both technically and operationally:

1. Live Obstruction Removal Notification to Loco Pilots: Integration with loco pilot consoles via secure communication channels (e.g., GSM-R, LTE-R) to provide real-time alerts directly to train drivers, allowing for immediate action and enhanced safety.

2. Night-Time and Low-Light Operation: Future iterations can incorporate infrared (IR) or thermal imaging cameras to extend functionality during low-visibility conditions such as fog, rain, or nighttime operations.

3. Obstacle Classification with Severity Index: Enhanced AI models can classify objects not only by type but also by risk level (e.g., "Critical – Large Object" vs. "Low – Plastic Debris"), helping prioritize response efforts by maintenance teams.

4. Automated Emergency Response Integration: Integration with railway control systems or SMS/IoT-based alerting services for automatic dispatch of inspection teams when a high-risk obstruction is detected.

5. Path Optimization and Auto-Navigation: Implementing GPS-based autonomous flight planning for drones to reduce human intervention, enabling scheduled patrols across large track networks.

6. Edge AI Integration: Moving detection models to onboard drone processors (like NVIDIA Jetson or Raspberry Pi with Coral TPU) to reduce latency and dependency on constant network connectivity.

7. Multi-Drone Fleet Coordination: Developing a centralized command system to coordinate a swarm of drones, allowing parallel inspection of vast railway networks and reducing overall monitoring time.

8. Integration with GIS and Predictive Maintenance: Storing historical detection data in GIS platforms to identify high-risk zones and support predictive maintenance strategies for recurring obstructions or terrain-based anomalies.

9. Cross-Domain Deployment: The system can be adapted for use in other sectors such as highway monitoring, pipeline inspection, border security, and agricultural land surveying with minimal modifications.

VII. CONCLUSION

The project Pinaka – An AI-Powered Aerial Surveillance System successfully fulfils its objective of enhancing railway safety by integrating real-time drone surveillance with deep learning-based threat detection. By combining autonomous video capture, object detection using YOLOv5 and Faster R-CNN, GPS mapping, and alert transmission, Pinaka delivers a practical, automated solution for identifying and reporting track obstructions. Built with a modular architecture using Python, Django, PyTorch, OpenCV, and MySQL, Pinaka offers a scalable and responsive system capable of operating under real-time constraints. Its ability to detect multiple hazards, geotag them with high precision, and alert relevant authorities in near real-time improves situational awareness and reduces human dependency in hazardous environments. The system's web-based interface further makes alert monitoring simple and accessible, even

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for non-technical staff. In conclusion, Pinaka demonstrates how AI and drone technology can be combined to create intelligent safety systems, paving the way for smart surveillance solutions in critical infrastructure monitoring.