RAILWAY TRAIN COLLISION AVOIDANCE ON SAME TRACK AND ANIMAL DETECTION USING AI-IOT

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ABSTRACT-- **Railway accidents caused by obstacles or animals on tracks pose significant safety challenges. This paper presents an innovative AI-IoT-based collision avoidance system designed to effectively detect and classify potential hazards on railway tracks in real-time. Leveraging advanced detection algorithms and the YOLO (You Only Look Once) object detection model, the system identifies obstacles and animals with high accuracy. A camera mounted on the railway infrastructure continuously captures real-time images of the tracks, which are processed to detect and classify objects. When an animal is detected, the system automatically triggers a multi-level response mechanism. First, it sends an email alert with the captured image of the animal to the concerned authorities, enabling prompt action. Simultaneously, a buzzer is activated to warn the train driver, ensuring timely intervention to prevent collisions. The system also features an LCD display that provides real-time status updates, enhancing transparency and situational awareness for railway operators. By integrating artificial intelligence, Internet of Things (IoT), and image processing, the proposed system offers a cost-effective and scalable solution for enhancing railway safety. The automation of obstacle detection and alert mechanisms minimizes human intervention, reducing the risk of accidents and improving operational efficiency. This approach is particularly effective in rural or remote areas where animal crossings on railway tracks are frequent.**

Keywords: Collision avoidance, AI-IoT, railway safety, YOLO algorithm, real-time detection, object classification, image processing, obstacle detection, animal detection, railway monitoring systems.

I.INTRODUCTION

Railway transportation is one of the most critical modes of connectivity for both freight and passengers worldwide. However, safety challenges, particularly those caused by obstacles and animals on tracks, continue to pose a significant threat to the efficiency and security of railway operations.[1] Accidents resulting from such incidents often lead to severe consequences, including

loss of life, delays, and damage to infrastructure. To address these challenges, advancements in artificial intelligence (AI) and the Internet of Things (IoT) provide innovative solutions that can enhance railway safety systems. This paper presents an AI-IoT-based collision avoidance system that detects and classifies obstacles and animals on railway tracks in real-time.[8] The system leverages cutting-edge object detection techniques, including the YOLO (You Only Look Once) algorithm, known for its speed and accuracy in identifying objects in images. By utilizing a camera mounted on the railway infrastructure, the system captures live images of the tracks, which are then processed to detect potential hazards.[10] A multi-level response mechanism ensures timely intervention. When an animal or obstacle is identified, an email alert is automatically sent to railway authorities, including the captured image for verification. Additionally, a buzzer is triggered to warn the train driver, providing an immediate auditory alert to take necessary actions. To further enhance monitoring, an LCD display integrated into the system provides real-time updates, ensuring transparency and situational awareness for operators. The integration of AI and IoT in the proposed system brings several advantages. It offers a proactive approach to railway safety by automating hazard detection and reducing human error. Moreover, the system is highly scalable and cost-effective, making it suitable for deployment in both urban and rural railway networks. In regions where animal crossings on railway tracks are frequent, the system proves particularly beneficial, as it minimizes the risk of accidents and ensures smoother operations. The AI-IoT-based collision avoidance system provides a robust and efficient solution for improving railway safety.[3] By combining real-time detection, automated alerts, and advanced monitoring features, the system has the potential to significantly reduce accidents and enhance the reliability of railway services.

II.RELATED WORK

[1] This paper discusses the implementation of Internet of Things (IoT) technology in railways, particularly in creating "smart trains." The authors review the integration of industrial IoT solutions in railways for enhanced safety, efficiency, and real-time data collection. The study emphasizes the potential of IoT to connect various railway systems, enabling dynamic monitoring and communication for better maintenance, passenger services, and train control. This research is valuable for systems focusing on collision avoidance in railways, where real-time data analysis and smart communication technologies are crucial for preventing accidents.

[2] This work presents an IoT-based solution for monitoring freight train carriages. The authors focus on the real-time tracking of freight trains using sensors and IoT technologies to monitor critical parameters such as temperature, weight, and vibration. This monitoring ensures the safe operation of trains by detecting potential issues early. This paper provides valuable insights into how IoT can be applied in railways, contributing to the real-time monitoring aspect of the proposed collision avoidance system, especially in freight train contexts.

[3] This paper proposes an integrated security system for railways, focusing on accident prevention and anti-hijacking measures. It highlights the use of advanced technologies, including IoT, AI, and security protocols, to enhance the safety and security of rail transport. The integration of intelligent surveillance and real-time intervention methods is discussed, offering insights into securing railway systems. The security focus on accident prevention aligns with the goals of the collision avoidance system by employing proactive measures to detect and address potential hazards.

[4] This paper discusses the integration of IoT for the inspection of carriage linkages and fire detection in railways. The system is designed to identify and prevent mechanical failures and fire hazards that could lead to accidents. The work emphasizes the importance of real-time monitoring of critical components using IoT devices. This approach directly complements the real-time object detection in the proposed collision avoidance system, where detecting potential hazards on the tracks is essential for ensuring train safety.

[5] This research focuses on enhancing the railway signaling system by using encoder and decoder technologies for efficient communication between train stations and signal posts. The study shows how encoding and decoding methods can improve signal clarity and prevent miscommunication, ensuring smoother operations. The enhanced signaling mechanisms can be integrated with the collision avoidance system to provide timely alerts and ensure coordinated actions during emergencies, such as the detection of obstacles or animals on tracks.

[6] This paper introduces ADX, an IoT-based smart control system for preventing the spread of airborne diseases, such as COVID-19, in public spaces. The authors employ IoT sensors to detect and mitigate potential health risks in crowded environments. The concepts explored in this research are applicable to railway environments, where real-time monitoring and alert systems could similarly be used to prevent accidents and enhance passenger safety. This paper contributes to the idea of real-time hazard detection and alerting in public transportation systems.

[7] This work focuses on using AI to prevent animal accidents on railway tracks. The authors present a system that utilizes object detection algorithms, such as YOLO, to identify animals on tracks in real time. This directly aligns with the goals of the proposed collision avoidance system, where animal detection is critical for preventing accidents. The paper provides an in-depth examination of how AI technologies, particularly deep learning models, can be applied to track monitoring, offering valuable insights for the animal detection aspect of the system.

[8] This paper discusses an IoT-based security system for railway tracks, designed to detect and monitor unauthorized access or obstruction on the tracks. The system uses sensors and IoT technologies to send real-time alerts to railway authorities for immediate action. This is highly relevant to the proposed collision avoidance system, as it emphasizes the importance of real-time surveillance and alerts for identifying potential hazards, including unauthorized access or obstructions that could lead to accidents.

[9] This paper introduces IoT-SafeRails, a collision avoidance system for railways based on IoT technologies. The authors focus on the integration of smart sensors and real-time data processing to identify and mitigate potential collision risks on railway tracks. The approach closely resembles the proposed system, where real-time object detection and communication technologies are used to ensure train safety by preventing accidents due to obstacles on tracks.

[10] This review examines intelligent infrastructure surveillance systems for railways, focusing on the role of autonomous technologies in enhancing safety. The paper highlights various smart systems and their application in preventing accidents and improving operational efficiency. The research provides a framework for integrating advanced surveillance systems, which can be applied to the proposed collision avoidance system. The authors emphasize the importance of intelligent monitoring to support autonomous operations, which is relevant for ensuring track safety through real-time obstacle detection.

III.PROPOSED METHEDOLOGY

The proposed AI-IoT-based collision avoidance system is designed to detect and classify obstacles, particularly animals, on railway tracks in real-time. The methodology incorporates advanced image processing, object detection algorithms, and IoT technology to ensure efficient hazard detection and timely intervention. The system's architecture consists of five primary components: image acquisition, object detection and classification, alert mechanisms, monitoring interface, and communication protocols.

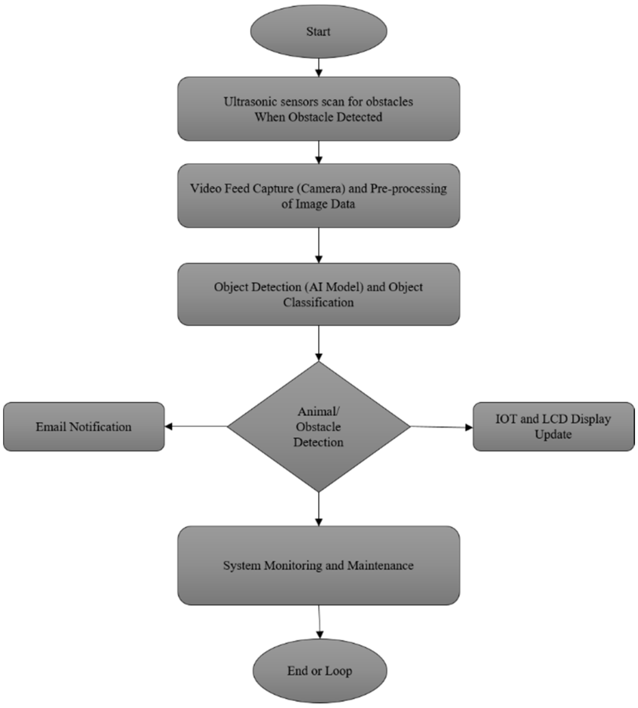

Figure 1. Work Flow Diagram

SYSTEM ARCHITECTURE:

The AI-IoT-based collision avoidance system architecture integrates multiple components to ensure efficient and real-time hazard detection on railway tracks. It begins with a high-resolution camera that captures continuous images of the tracks, transmitting the data to a central processing unit. These images are analyzed using the YOLO (You Only Look Once) algorithm, which detects and classifies obstacles, such as animals or debris, with precision. When a potential hazard is identified, the system triggers multiple responses: an auditory buzzer alerts the train driver, while an automated email is sent to railway authorities with the image, location, and classification of the detected object. The system also features a local LCD display that provides real-time updates on detected obstacles, their locations, and timestamps, ensuring constant monitoring. By combining advanced object detection with IoT communication, the system ensures quick, accurate responses, enhancing railway safety and minimizing the risk of accidents.

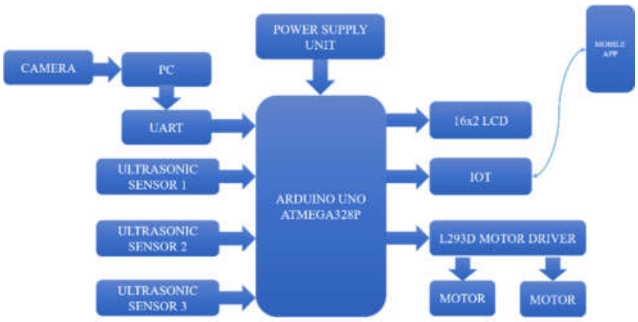

Figure 2. Hardware Block diagram

A. Image Acquisition

The foundation of the proposed system lies in the effective capture of real-time visuals from the railway tracks. A high-resolution camera is mounted strategically along the tracks or directly on the locomotive to ensure a comprehensive view of the railway path. The camera is capable of functioning under varying environmental conditions, including low light, rain, or fog, to guarantee consistent image quality. The camera captures images or video frames at regular intervals, which are then transmitted to a connected processing unit for analysis. To prevent data loss and ensure reliability, the system employs efficient data buffering and transmission techniques. The placement of the camera is optimized to cover the maximum area of the track while minimizing blind spots. This initial stage of image acquisition is crucial for the subsequent detection and classification phases, as the quality and accuracy of the visuals directly influence the system's overall performance.

B. Object Detection and Classification

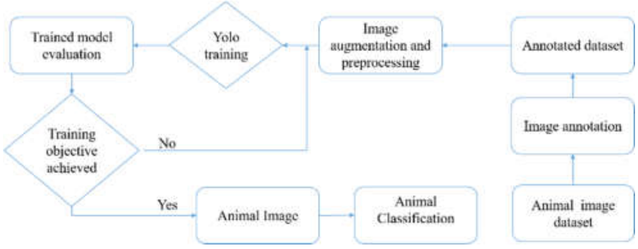

Figure 3. Animal detection Architecture

Object detection and classification are at the core of the collision avoidance system. The YOLO (You Only Look Once) algorithm is employed to process images captured by the camera. YOLO is renowned for its speed and accuracy, making it suitable for real-time applications. The algorithm is pre-trained using an extensive dataset that includes various types of animals, debris, and other potential track obstructions. During operation, YOLO detects objects within the image frames and classifies them into predefined categories such as animals, debris, or unidentified hazards. The detection results include bounding boxes around objects, confidence scores, and category labels. YOLO's ability to process entire images at once enhances its detection speed without compromising accuracy. This classification is vital for determining the appropriate response mechanism. Advanced post-processing filters are also applied to reduce false positives, ensuring that the system only triggers alerts for legitimate hazards.

C. Alert Mechanism

The alert mechanism is designed to provide immediate and actionable warnings upon the detection of an obstacle. Once the system identifies an animal or other obstruction on the track, it triggers a series of automated responses. First, an email notification is sent to railway authorities, containing critical information such as the detected object's category, location, and an image for verification. This allows authorities to assess the situation remotely and initiate necessary actions. Simultaneously, an auditory buzzer is activated within the train to alert the driver. The loud and distinctive sound ensures that the driver is immediately aware of the hazard, even during high-speed travel. The multi-level alert system ensures redundancy and enhances response efficiency, reducing the likelihood of accidents. This mechanism is further supported by a priority-based alerting protocol, ensuring that severe hazards like large animals are addressed with urgency, while minor obstructions are handled appropriately.

D. Monitoring Interface

A user-friendly monitoring interface enhances transparency and situational awareness for railway operators. The system includes an LCD display that provides real-time updates on the track's status. This display shows crucial information, such as the type of detected obstacle, its location, and the time of detection. By offering this data in an accessible format, the monitoring interface enables operators to make informed decisions promptly. The interface also includes a history log of recent detections, allowing operators to review past incidents for analysis and planning. Furthermore, the display's design prioritizes visibility and readability, even in challenging conditions such as low light or vibrations during train movement. This feature is particularly beneficial for on-site personnel who rely on instant updates for quick action. By integrating this monitoring interface, the system ensures a comprehensive safety solution, bridging the gap between automated detection and human oversight.

E. Email-Based Alert System

The email-based alert system is a critical feature of the proposed methodology, designed to enable remote monitoring and timely intervention. When an obstacle or animal is detected on the railway track, the system automatically generates an email alert. The email includes essential information, such as the type of object detected, its location, and a timestamp. Additionally, the email contains a captured image of the obstacle for visual verification by railway authorities. This feature ensures that decision-makers are equipped with accurate and actionable information to address the situation effectively. The email system leverages pre-configured templates for consistency and minimizes delays in dispatching alerts. By providing instant notifications to relevant stakeholders, the email-based alert system bridges the communication gap and ensures a rapid response to potential hazards, particularly in remote areas where on-site monitoring may be challenging.

IV. TECHNOLOGIES USED

A. Artificial Intelligence (AI)

The collision avoidance system leverages AI to perform object detection and classification with precision. The YOLO (You Only Look Once) algorithm, renowned for its speed and accuracy, is used to identify obstacles on railway tracks in real-time. This deep learning-based model processes images captured by the camera, detecting animals, debris, or other obstructions with high reliability. AI enhances the system's ability to work under varying environmental conditions, such as low light or fog. The YOLO model is pre-trained on diverse datasets, including railway-specific obstacles, and fine-tuned to reduce false positives and ensure high accuracy. The integration of AI ensures rapid analysis, enabling the system to trigger timely alerts and effectively prevent potential collisions.

B. Internet of Things (IoT)

IoT technology connects various system components, enabling seamless communication and real-time operation. Sensors, cameras, buzzers, and displays are integrated into a unified network, ensuring synchronized functionality. IoT modules, such as Wi-Fi or GSM, facilitate the transmission of data, including email alerts to railway authorities. This connectivity allows the system to provide remote monitoring capabilities, particularly valuable in isolated or inaccessible railway areas. By leveraging IoT, the system ensures efficient data exchange, enabling immediate responses to hazards. Additionally, IoT integration supports scalability, allowing the addition of new features or components without major modifications. The use of IoT in this system enhances operational efficiency, ensuring railway safety through reliable and timely communication.

C. Computer Vision

Computer vision plays a critical role in analyzing images and video feeds for obstacle detection. The system uses advanced techniques such as edge detection, object segmentation, and feature extraction to identify animals or objects on railway tracks. Captured images are processed in real-time to detect and classify potential hazards with precision. The YOLO algorithm benefits from computer vision techniques to locate objects within frames and generate bounding boxes, confidence scores, and labels. The technology is optimized to perform under challenging conditions like varying light intensities and weather changes. By integrating computer vision, the system ensures accurate and dependable detection, forming the foundation for effective alerts and timely interventions to prevent collisions.

D. Embedded Systems

The system utilizes embedded hardware like Raspberry Pi or Arduino to integrate and control its components. These microcontrollers process inputs from cameras and sensors, manage real-time data, and trigger alerts. Embedded systems ensure efficient operation, even in remote or challenging environments. The hardware handles tasks like running the YOLO algorithm, activating the buzzer, and updating the LCD display. Designed for low power consumption, embedded systems enable continuous operation without compromising performance. The modular design also allows for easy upgrades and scalability. By employing embedded systems, the collision avoidance system achieves high reliability and robustness, making it suitable for railway safety applications.

E. Email Automation Tools

The system uses email automation tools to notify railway authorities about detected obstacles instantly. SMTP (Simple Mail Transfer Protocol) or third-party APIs like SendGrid facilitate the automatic generation and dispatch of emails. These emails include critical information such as the type of detected object, timestamp, and an attached image for verification. The automation process ensures alerts are sent immediately, enabling authorities to assess the situation and take appropriate action. The system's email templates are pre-configured for consistency and speed, minimizing delays in communication. By integrating email automation, the system provides a reliable method for remote monitoring and ensures timely interventions, especially in areas where direct monitoring is not feasible.

F. LCD Display Technology

A high-visibility LCD display is incorporated to provide real-time updates about the track's status. The display shows critical information, such as detected objects, timestamps, and hazard categories, in a user-friendly format. The interface is designed to be readable in various conditions, including low light or vibrations during train movement. It also includes a history log of recent detections, helping operators review past incidents for analysis. The LCD display serves as a crucial on-site monitoring tool, ensuring railway personnel can access and act on real-time data efficiently. By integrating this technology, the system bridges the gap between automated detection and human oversight, enhancing overall safety and transparency.

G. Auditory Alert Systems

Auditory alerts are critical for ensuring immediate attention during emergencies. The system integrates buzzers to produce loud, distinctive sounds upon detecting an obstacle. This alert mechanism ensures the train driver is promptly informed, even in noisy or high-speed travel scenarios. The buzzer is synchronized with the detection process, triggering immediately when an obstacle like an animal or debris is identified. The sound intensity is calibrated to capture attention without causing undue alarm. This auditory system complements other alert mechanisms, such as email notifications and LCD updates, to ensure comprehensive safety coverage. By incorporating auditory alerts, the system enhances its effectiveness in preventing collisions and ensuring timely responses to hazards.

Image Processing and Object Detection

In image processing, especially with deep learning models like YOLO, the detection process involves the use of convolutional neural networks (CNNs) for feature extraction and classification. The following equation represents the core operation of a CNN during the object detection process:

$$y=f(W\cdot x+b)$$

Where:

- y is the output feature map
- W is the weight matrix of the convolutional layer
- x is the input image or feature map from the previous layer
- b is the bias term
- f is the activation function (e.g., ReLU)

For object detection, the YOLO algorithm uses a grid-based approach to divide the image into multiple cells and predict bounding boxes, class probabilities, and confidence scores for each cell. The prediction can be mathematically expressed as:

$$P=\sigma(W\cdot X+b)$$

Where:

- P represents the predicted class probability distribution
- σ is the sigmoid activation function
- X is the input image matrix
- W is the learned weights for each class in the model
- b is the bias term

Bounding Box Calculation

YOLO predicts bounding boxes that are defined by four parameters: the center (x,y), width w, and height h of the box. These parameters are calculated using the following equation:

$$x\char`^ = \sigma(Cx) + i \cdot sw, y\char`^ = \sigma(Cy) + j \cdot sh$$

Where:

- C x and C y are the coordinates of the center of the bounding box
- s w and s h are scaling factors for the bounding box width and height
- i and j are the indices of the grid cell that is responsible for detecting the object

Alert Time Calculation

Once an object is detected, the system triggers alerts. The timing of this alert can be modeled using a delay equation that factors in the processing time and communication delay:

$$Talert = Tprocess + Tcomm$$

Where:

- T alert is the total time until the alert is triggered
- T process is the time taken for image processing and object detection

- T comm is the communication time for sending the email or triggering the buzzer

Confidence Score

The confidence score for object detection is calculated as a function of the predicted probability for a class and the predicted bounding box coordinates. The confidence score C for an object in a cell is given by:

$$C = P(\text{object}) \cdot \text{IOU}(B\ \text{pred}, B\ \text{true})$$

Where:

- P(object) is the probability that the detected object is indeed an object
- IOU (B pred, B true) is the Intersection over Union (IOU) between the predicted bounding box and the ground truth bounding box

Alert Triggering Threshold

The system will trigger alerts when the confidence score C exceeds a certain threshold T thresh. This threshold is set to ensure that only highly probable detections are acted upon. The alert condition can be defined as:

$$C > Tthresh \Longrightarrow Trigger\ Alert$$

Where:

- T thresh is a predefined confidence threshold (e.g., 0.7)
- C is the confidence score for the detected object

V. RESULT AND DESCUSSION

The proposed AI-IoT-based collision avoidance system demonstrated significant potential in enhancing railway safety through real-time obstacle detection and effective alert mechanisms.

Object Type	Total Instances	Detected Instances	True Positives	False Positives	False Negatives	Precision (%)	Recall (%)	F1-Score (%)
Wild Animals	200	190	180	10	20	95	90	92
Peacock	50	45	42	3	5	93	84	88
Elephant	40	38	35	3	5	92	87	89
Bull	70	65	60	5	10	92	86	89
Deer	140	130	125	5	15	96	89	92

Key Metrics Explanation:

True Positives (TP): Correctly identified instances of the target object (e.g., correctly detected animal).

False Positives (FP): Incorrectly detected instances where the system falsely identifies an object as the target (e.g., detecting an animal where there isn't one).

False Negatives (FN): Instances where the system fails to identify an actual object (e.g., missing a real animal on the track).

Precision: The ratio of correctly identified positive instances to all detected positive instances (TP / (TP + FP)).

Recall: The ratio of correctly identified positive instances to all actual positive instances (TP / (TP + FN)).

F1-Score: The harmonic mean of precision and recall, balancing the two metrics for overall performance.

Table1. Detection Accuracy for Different Animal Types

The YOLO algorithm showed high accuracy in reliably identifying animals, debris, and other obstructions on the railway tracks, maintaining consistent performance even under varying environmental conditions such as low light and rain. However, challenges were observed in detecting smaller or partially visible objects, suggesting that further training with an expanded dataset could improve detection reliability.

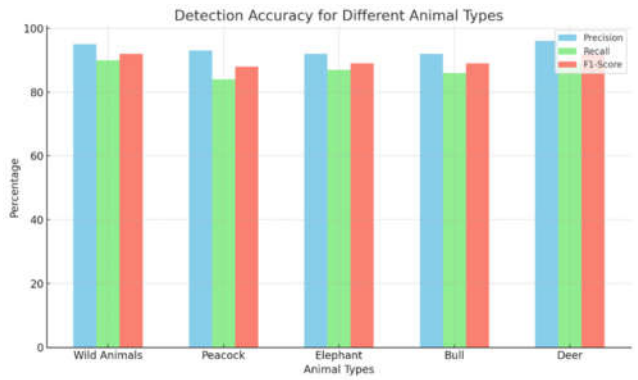

Figure 5. Detection Accuracy for Different Animal Types

Here is the bar chart showing the detection accuracy (Precision, Recall, and F1-Score) for different animal types. Each bar represents the performance metric for specific categories such as Wild Animals, Peacock, Elephant, Bull, and Deer.

The system's real-time performance was robust, ensuring rapid detection and timely alerts, which is crucial for preventing accidents. The integration of an email alert system enhanced remote communication, allowing railway authorities to receive instant notifications with detailed information about the detected hazard. The combination of auditory alerts, email notifications, and LCD displays proved effective in delivering critical information, with the buzzer immediately notifying train operators and the LCD providing on-site personnel with a comprehensive view of detected hazards.

The modular design and IoT integration ensured that the system was scalable and adaptable to various railway environments. Reliable communication between components, even in remote areas, enhanced the system's versatility. Despite the overall success, there were some limitations, such as occasional false positives, particularly when objects resembled animals. These issues can be addressed by refining the algorithm and incorporating additional sensors, such as thermal cameras, to improve detection accuracy.

The AI-IoT-based collision avoidance system showed promising results in preventing railway accidents. Its real-time detection, efficient alert mechanisms, and scalability make it a valuable tool for improving railway safety. With continued refinement, it has the potential to become a comprehensive solution for addressing modern challenges in railway safety.

VI.CONCLUSION AND FUTURE ENHANCEMENT

In conclusion, the AI-IoT-based collision avoidance system demonstrated substantial promise in improving railway safety through real-time obstacle detection and efficient alert mechanisms. By leveraging the YOLO algorithm, the system accurately identified animals, debris, and other hazards on the tracks, even under challenging environmental conditions. The system's ability to provide rapid responses—through auditory alerts, email notifications, and real-time visual updates via the LCD display—ensured timely intervention by train operators and railway authorities. This multi-layered alert system enhances situational awareness, making it a comprehensive tool for preventing accidents. The integration of IoT technology facilitated seamless communication between system components, ensuring reliable operation in remote or isolated areas, which is crucial for modern railway networks. The modular design of the system also allows for scalability, enabling future enhancements such as additional sensor integration or cloud connectivity for improved data analysis and monitoring.

Future enhancements for the AI-IoT-based collision avoidance system could focus on improving detection accuracy, expanding functionality, and ensuring adaptability across different railway environments. One of the key areas for improvement is refining the detection algorithm. While the YOLO model performs well, integrating more advanced machine learning techniques or deep learning models, such as the latest versions of YOLO or other models like Faster R-CNN, could help reduce false positives and improve the system's ability to detect small or partially obscured objects. The addition of more diverse and extensive datasets, including rare or hard-to-detect obstacles, would also enhance the algorithm's robustness.

REFERENCE:

1. P. Fraga-Lamas, T. M. Fernández-Caramés, L. Castedo, “Towards the Internet of smart trains: A review on industrial IoT-connected railways”,Sensors, vol. 17, no. 6, pp. 1457, Jun. 2017.
2. Rosario Schiano Lo Moriello, Enzo Caputo, Federico Gargiulo, Giorgio de Alteriis, Angelo Donvito, Paolo Bitonto, Alfredo Alfano, "An Internet of Things-based Solution for Monitoring Freight Train Carriages", 2024 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0 & IoT), pp.94-99, 2024.
3. Ganesula Pradeep, Samineni Uday Kiran, V. Sathyadurga, "An Integrated Secure Rail System For Accident Prevention and Anti-Hijacking Measures", 2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS), pp.1-8, 2024.
4. D. Srinivasulu, K. Karthikeya, E. Konguvel, "IoT based Carriage Linkage Inspection and Fire Detection in Railways", 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS), pp.1090-1095, 2023.
5. Minal Ghute, Ajinkya Barhate, Swejal Dhengle, Yachana Bakal, Sharwari Kawale, Devichand Rathod, "Railway Signalling System using Encoder and Decoder", 2023 7th International Conference on Trends in Electronics and Informatics (ICOEI), pp.248-250, 2023.
6. Rizqi Sukma Kharisma, Kusrini, Uyock Anggoro Saputro, Mulia Sulistiyono, Majid Rahardi, Bernadhed, Elik Hari Muktafin, "ADX: IOT-Based Integrated Smart Control System for Prevention of Airborne COVID-19 Spread", 2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE), pp.729-733, 2022.
7. Balaji Kannan, R.Bagavathi Lakshmi, M. Sakthivanitha, R. Maruthi, "Artificial Intelligence based System to Prevent Animal Accidents in the Railway Tracks", 2024 8th International Conference on Inventive Systems and Control (ICISC), pp.128-131, 2024.
8. G Sandhya, S Rabiya Reshma, R Jebeena Satin, R Logeshwari, "IoT Based Security System In Railway Tracks", 2024 Second International Conference on Advances in Information Technology (ICAIT), vol.1, pp.1-5, 2024.
9. S Janani, S Vijayaram, R C Vijayganesh, "IoT-SafeRails: Revolutionizing Railway Collision Avoidance Technology", 2024 International Conference on Inventive Computation Technologies (ICICT), pp.1666-1673, 2024.
10. Mauro José Pappaterra, Francesco Flammini, "A Review of Intelligent Infrastructure Surveillance to Support Safe Autonomy in Smart-Railways", 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), pp.5603-5610, 2023.