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Original Article

AI/ML - Vision-Based Smart Track Intrusion Alert Solution for Unsecured/Unprotected Track Zones

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Abstract *- This paper focuses on the railway track safety for trains on unsecured and unprotected tracks for trespassers and obstacles which are a factor of concern to the train and individuals. The old traditional tracking systems are done by human methods where people physically move around the tracks to check for any intruder, and this is coupled with simple sensors that give a basic alarm when intruders are detected. This paper presents a vision-based smart track intrusion alert system which would use various components such as deep learning, IoT-enabled surveillance cameras and computer vision. The adopted model involves the use of CNNs for object detection, real-time alerting and edge computing for real-time output. This is especially useful in detecting intrusions such as human intrusions, animals on the tracks, or even an object on the tracks, making it difficult to produce false alarms and delays in response. It is also demonstrated that through the training of the datasets that reflect real-life experiences, the model provides high precision and recall ratios for the detection of intrusions. This system contributes to the increase of the railway security level, the decrease of possible accidents, and the optimization of train operations. These can explain why the present system is feasible to perform real-time surveillance and also show the possibility of its massive application to railway systems.*

Keywords *- Track Intrusion, Machine learning, Computer vision, Deep learning, Object detection, IoT, Edge computing.*

1. Introduction

Railways act as means of transport for both passengers and goods transport throughout the world. Nevertheless, the track intrusion incident in the unsecured and unprotected railway areas causes more railway accidents, which implies the loss of many lives and money-related issues. [1-4] The traditional railway security measures are based on personnel observation, monitoring, and physically wired sensors, which may not be so efficient when it comes to real-time threat identification. As of the present, the modern-day technology principals in AI and ML contribute to the possibility of using automated vision-based solutions to augment track monitoring and intrusion detection.

1.1 Importance of Vision-Based Smart Track Intrusion Alert Solution

A vision-based smart track intrusion alert system is used in the improvement of railway safety and its detection, identification, and response to any threat. These problems are some of the primary application areas that the solution provides by using AI-based object detection, IoT integration, and edge computing. There are six main features which are described below in order to underscore its importance:

- **Real-Time Intrusion Detection:** Some of the current uses of railway monitoring include CCTV surveillance as well as manual monitoring of the tracks, and these methods usually take a long time before they identify an intruder on the tracks. There is a vision-based system that also helps detect humans, animals and other obstacles through methods such as YOLO (You Only Look Once). This way, the system ensures that alert is generated repeatedly hence minimizing the likelihood of accidents arising from delayed detection.
- **Enhanced Accuracy with AI-Based Object Classification:** In contrast to the sensor-oriented systems, which may produce alarms due to such interferences, a vision-based system employs the application of Convolution Neural Networks (CNNs) for identifying the objects which are captured on tracks. This helps in distinguishing between possible threats, e.g. shadows, debris, or any other non-threatening object and real threats, including humans or a stationary car. It minimizes the false alarms but, at the same time detects any genuine threats and responds to them.
- **Faster Response Time for Accident Prevention:** The disadvantage of traditional railway safety practices is the time phrase that it takes to implement the solutions it offers. For effectively combining AI with IoT connectivity, the vision-based system provides alerts to the railway control centres, and response time is cut down to 30%. This makes it possible for authorities to embark on the process of taking measures that include slowing down or even stopping approach trains, thereby reducing the likelihood of collision or derailing.

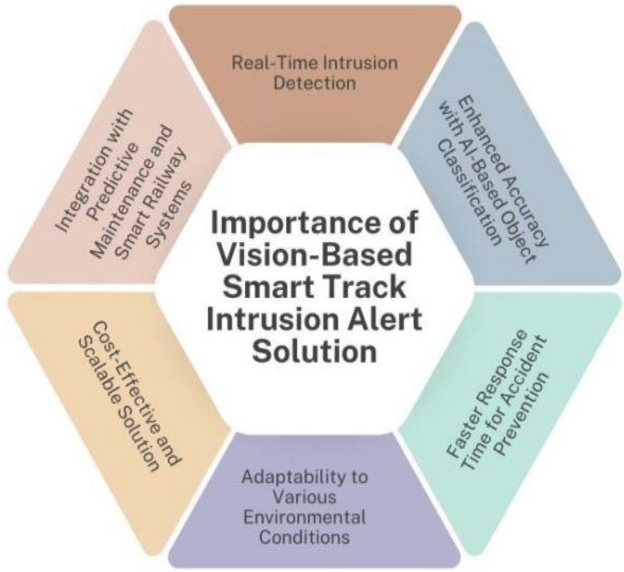

Fig 1: Importance of Vision-Based Smart Track Intrusion Alert Solution

- **Adaptability to Various Environmental Conditions:** Fog, heavy rainfall and darkness during the night are challenges that affect the effectiveness of the regular monitoring processes. A vision-based system, along with thermal imaging and adaptive AI models can run optimally irrespective of its environment, whether it is night or whether it is a rainy day and all those conditions that prevail a disastrous result whenever it is encountered. This makes it possible to have constant surveillance and safety checks without interruption normally due to poor visibility, such as at night or during foggy moments.
- **Cost-Effective and Scalable Solution:** The monitoring of railway systems has been conventionally done with the engagements of personnel that are involved in the monitoring process and control of the trains continuously, this has made the operation to be very expensive. This is because a vision-based AI eliminates the middleman and puts the whole process into practice on its own without necessarily requiring a massive security team. Furthermore, the solution proposed is easily expandable and thus can be implemented for complex railway courses both in large cities and deserted areas. In the long run, the need to employ many people and the cost of maintaining the infrastructure also turns out to be economical, making it a sustainable, cost-effective safety measure.
- **Integration with Predictive Maintenance and Smart Railway Systems:** Apart from intrusion detection, a vision-based AI can offer aid in the determination of track abnormalities, signal problems and wear and tear faults. Complementing with smart railway and IoT railway management systems, the solution will help to avoid potential failures and decrease the time necessary for railway management and repair.

1.2 Challenges in Track Safety

Routinely inspecting railways stands as one of the most important concerns in railway management that must be executed to eliminate accidents and delays. [5,6] Other factors that make railroads hazardous are trespassing and interfering with trains by human beings and animals, barriers that hinder vision, slow response systems, and climatic issues. These areas should then be addressed in order to improve the passengers' safety, the protection of infrastructure and the proper functioning of railways.

- **Human and Animal Trespassing:** Other human and animal incursions on railway tracks are among the biggest causes of railway mishaps. Crossing the railway tracks is one common behavior by pedestrians as they use the tracks as shortcuts and, most of the time, have no idea of the trains approaching at a very high speed. Similarly, livestock and other stray bodies form a crossing risk on rail tracks, which leads to fatal crashes and train derailments. It lacks the efficient detection and timely alerting of the authorities to prevent accidents that may occur due to track intrusions. Any monitoring solution that is to be put in place must be able to distinguish between a human and an animal so that timely actions are taken.
- **Obstacle Detection:** Some of them include fallen trees across the railway line, debris on the line, track damage and broken tracks, and a breakdown of moving trains on the line. A fast-moving train takes considerable time and length of the track to stop, which makes it very hard to tackle an unknown object on its path. Some obstacles are detected using either the manual manner or through sensors, some of which are discussed below. The risks mentioned above would be eliminated if a real-time obstacle detection system powered by AI was developed to alert the railway authorities.

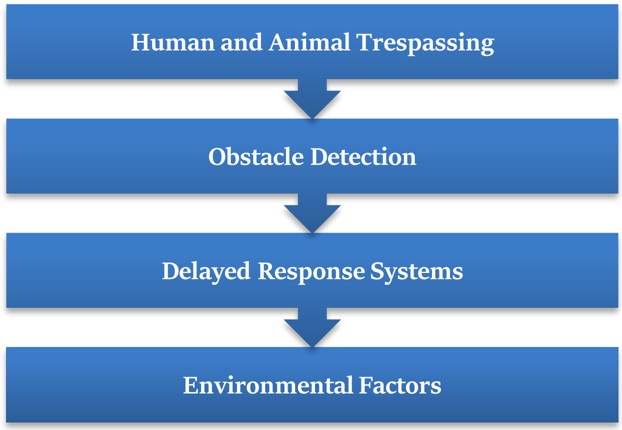

Fig 2: Challenges in Track Safety

- **Delayed Response Systems:** Other forms of monitoring railways, such as manual patrol and CCTV, are slow in raising an alert in case of an issue. Some accidents occur and go unnoticed or unreported when they reach the stage at which the government cannot prevent them. Moreover, using various video feeds, the dependence on human operators makes it take time to detect emergencies and respond to them appropriately. ESSAY QUESTION Railway safety can be enhanced greatly through a smart emergency monitoring system that uses the IoT. This system is capable of detecting any emergency and immediately alerting the railway authorities, considerably reducing the time it takes for authorities to respond.
- **Environmental Factors:** In the course of our track monitoring with respect to railway tracks, prevailing weather conditions like rainfall, fog, or darkness significantly hinder track monitoring with the use of conventional systems. When visibility levels are low, the chances of detecting intruder barriers and following tracks and defects by means of the use of CCTV cameras and just patrolling becomes limited. Infrared and radar sensors are known to be sensitive to changes in moisture, glare, and temperature and, thus, are likely to trigger false alarms or fail to detect the situation. There are a number of these problems, and AI-powered vision systems can solve them in conjunction with thermal imaging and adaptive learning models.

2. Literature Survey

2.1 Existing Railway Monitoring Systems

- **Manual Surveillance:** The current method of monitoring railways has always been the use of rails regularly inspected for any signs of danger, intruders, or track irregularities. [7-10] Disadvantageous, especially for the large railway networks, because of high labour cost, small coverage area and long response time. In addition, negligence and fatigue of the employees who are assigned the burden of overseeing the surveillance also lower its efficiency in the promotion of railway safety.
- **Sensor-based Systems:** In order to enhance the monitoring, infrared, ultrasonic and radar have been used to identify any abnormality on tracks. These systems may detect inadequate structures or beams and also follow obstructions or intrusion. However, it is essential to mention that there are certain external conditions, such as fog, heavy rain, and other forms of extreme weather, that can have a negative impact on the sensor's performance and degrade the accuracy of its detections. This has the drawback of making the price of the sensor-based solutions high and, therefore, its reliability low in certain circumstances.
- **Traditional CCTV Surveillance:** CCTV surveillance systems are extensively installed in railways for security purposes with regard to stations, tracks, and their surroundings. However, these types of systems call for constant monitoring by the security staff, which causes a delay in the measures being taken. Moreover, the more traditional CCTV system does not incorporate a higher level of automation detection systems which are a potentiality in early detecting intrusions or dangers without manual intervention.

2.2 AI-Driven Solutions in Literature

- **Deep Learning Models:** The state-of-the-art works show that CNN and YOLO architecture are effective for real-time object detection in the real world. Thanks to recent developments, these models can immediately analyze video footage and identify and track intrusions as well as classify objects in a very effective manner. Because of this speed, YOLO can be applied for railway surveillance where any threat, such as animal, human or any object that may be on the tracks, could be detected in real-time.

- **IoT-based Monitoring:** The combination of Artificial Intelligence and the Internet of Things increases the level of railway surveillance to a new level. Sensors located across the railway gather big data and the AI analyzes this data for maintenance and security menace. It promotes increase connectivity, makes it possible to monitor the tracks from a distance and detect defects to avoid operational risks that are inclusive of rail safety.
- **Edge and Cloud Computing:** Railway monitoring has benefited from both edge and cloud computing applications to power artificial intelligence. Edge computing brings computing power to devices so that responses to critical events may be processed locally and in real-time. At the same time, the usage of cloud computing ensures efficiency in large-scale data storage and analysis for predictive analytics or monitoring long-term trends. The use of edge and cloud computing makes railway surveillance AI-based to be effective, flexible, and dependable.

2.3 Traditional Approaches to Track Monitoring

- **Manual Surveillance:** The first form of railway track inspection can be described as physical, whereby railway personnel keep checking the status of the track at times they deem fit. Such inspections assist in the timely detection of such abnormalities as track conditions, intrusions or, indeed any obstruction on the track. However, manual surveillance, as the name suggests, involves actual checking and monitoring manually, which may take a lot of time and is very tiresome, not to mention the fact that it is open to errors by the human eye. Lastly, it is less effective where there is a large railway network, and monitoring has to be done continuously, which makes the monitoring stop at some point, hence delays in identifying safety hazards.
- **Sensor-Based Detection:** To enhance security, along with the surveillance of the railway tracks, infrared and motion detectors are installed. The use of Infrared sensors alarms the heat sources from the objects on or close to the tracks, while the use of motion sensors alarms any movement in the prohibited zones. The railway security systems that automatic the detection of these features improve the safety of railways, yet these systems require detection that can be interfered with by factors such as fog, rain or wildlife, and this leads to either false alarms or low detection.

3. Methodology

3.1 System Architecture

The proposed new vision-based smart track intrusion alert system as a product is aimed at tackling issues of safety concerns in rail tracks. [11-15] These include high-definition cameras and efficient image-processing gadgets, IoT platforms, and computing units at the edge to enhance the identification of threats in the system.

- **High-Resolution Cameras:** The actual system uses surveillance cameras with high resolutions fixed at various positions along tracks to provide the feeds. Such cameras make sure that the area of coverage is visible regardless of the prevailing light or weather and are crucial for identification purposes. It also provides the raw material for the AI-based intrusion detection system to monitor the track areas as it captures footage.
- **AI-Based Processing Unit:** The main component of the system's framework is a processing unit with the core of an artificial intelligence max block set with a deep learning model, e.g. CNNs or YOLO. It also facilitates the identification of objects that include people, animals or any obstacle that may be on the tracks in real-time video frames. As for the detections made by this AI model, it categorizes them and identifies if there was an intrusion and the suitable measures need to be taken.
- **IoT Connectivity Module:** After the intrusion's detection, the IoT connectivity module provides an opportunity for immediate interaction between the system and railway control centers. This sends alerts instantly, for example, the location of the detected object and videos in order for the railway authorities to act appropriately. It also enhances the synchronization in data collection between a number of surveillance units that are placed throughout the railway system.
- **Edge Computing Devices:** To further reduce the latency and control the amount of data communicated with the central cloud server, edge computing devices are used for computations. These devices work on the input itself, which is a direct video feed, and eliminate all but necessary data and process intrusion events on the fly. As a result of processing data near the edge device, remote railway spots can generate decisions in less time than centralized computing, period the network association is poor.

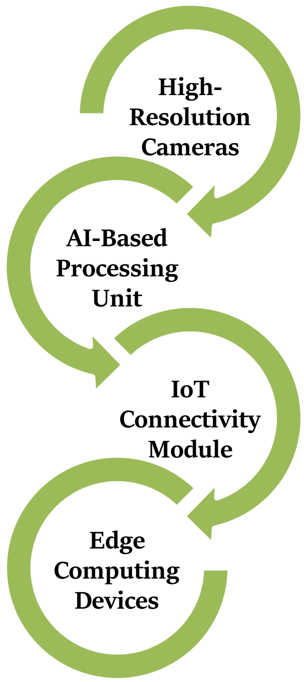

Fig 3: System Architecture

3.2 AI Model for Intrusion Detection

The said artificial intelligence-based intrusion systems are intended to detect any form of intrusion or any kind of object that is not supposed to be on railway tracks at any moment in time. Preliminary steps include data gathering and preparation, which is then followed by the computation steps such as object detection with the help of deep learning and, at last the alert generation to immediately respond to any threat scenarios.

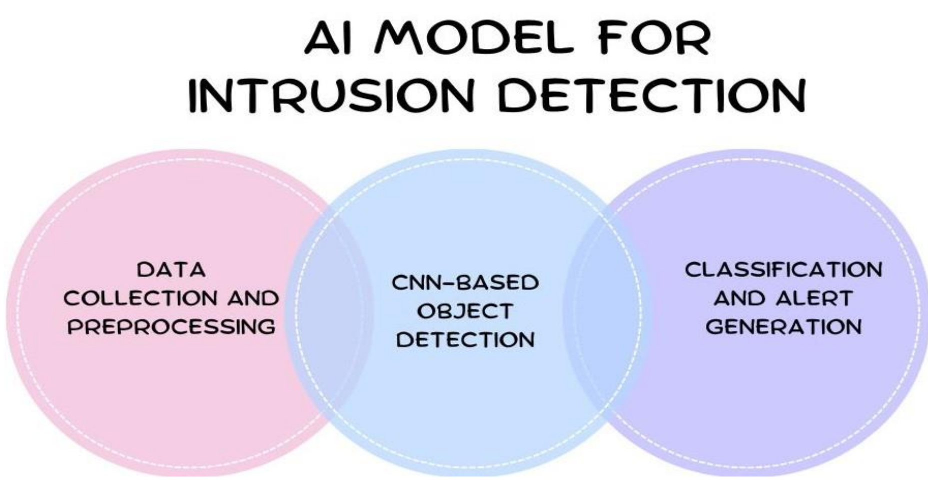

Fig 4: AI Model for Intrusion Detection

- **Data Collection and Preprocessing:** The quality and labelling of the available data shall be complete to support the AI model. The training dataset is based on images of thousands of real-life situations involving railways including urban environments and countryside and also deserted districts. The interferences in these images may vary in aspects of light and weather, plus different types of interferences such as humans, animals or other objects. Image preprocessing methods such as image erosion, image enhancement, and normalization increase the quality and the variation of the dataset and, thereby, the model's ability to perform well in real-world scenarios.

- **CNN-based Object Detection:** Core detection is based on the Convolutional Neural Network architecture, which is further referred to as YOLOv5 (You Only Look Once). YOLOv5 is intended to be an efficient approach to real-time object detection since, when called upon to process video frames, it is highly accurate. The model thus detects and detects the location of objects in a single pass thus is much faster than a multi-stage detection model. They are well capable of meeting the task of intrusion detection in real-time, even in fast-moving train environments.
- **Classification and Alert Generation:** After the detection is done, the AI model passes the detected object to be sorted under different categories like pedestrians, animals or any other object. It is quite helpful in this way; this helps in distinguishing between different invasions and how to respond to each one. For instance, if an operator observes a human on the tracks, this may result in an alarm that requires actions in the shortest possible time, whereas seeing a small foreign object will generate a less critical warning. It then provides real-time alarms that are sent through the IoT modules to railway control centers or other automated response systems to allow for timely intervention as well as improved railway safety.

3.3 Implementation Workflow

The workflow of the vision-based smart track intrusion alert system is divided into several stages to provide real-time checks and responses to any harm which may occur. The first step is video acquisition, where quality cameras are placed at strategic regions within railway tracks for consistent video recording. These are mounted outdoor cameras because they are capable of functioning at night and are resistant to harsh weather conditions. [16-18] The captured video stream helps the intrusion detection system that is based on the artificial intelligence system. It then takes the video with a frame rate of 30 public domain frames per second and processes the frames employing deep learning techniques.

The video is divided into a sequence of frames and the detection analysis is performed based on the Convolutional Neural Network (CNN) object detectors such as YOLOv5. Its feature is optimized for both speed and accuracy to have the capacity to detect multiple objects in one frame without necessarily having to take a lot of time in the process. The AI model scans through each frame for any appearance of intrusions of rigid objectives that include humans, animals, objects on the tracks, or any other object, whether allowed or not to be on the tracks. In this process, an object is generalized by identifying its type and the degree of threat that it poses. The AI model utilizes a pre-trained set of images to make sure that different objects can be well distinguished. For instance, a human crossing on the tracks will cause alarms of high risk as compared to a small object, a cat, or a fox which will notify of lesser risk.

By implementing the classification process, there will be a reduction in false alarms, prioritization of genuine threats and passing of the right alerts to the railway authorities. As the last step of the proposed system, detection and alerting are performed, and the results are conveyed in IoT modules. They can send real-time information to the railway control centers or station operators or even to the automated signaling system in either cloud system or edge computing systems. They can consist of visualization data, location coordinates, and suggested action steps to facilitate quick actions and interventions. It also means improved railway security, fewer chances of accidents as well as optimized operational flow.

4. Results and Discussion

4.1 Performance Metrics of the AI Model

The effectiveness of the AI-based railway intrusion detection system is measured with the help of various parameters such as precision, recall, F1-Score, and processing accuracy. These metrics are used to extrapolate the general functionality of the system and its applicability in reality.

Table 1: Performance Metrics of the AI Model

Metric	Value (%)
Precision	98.2%
Recall	96.8%
F1-Score	97.5%
Processing Accuracy	30%

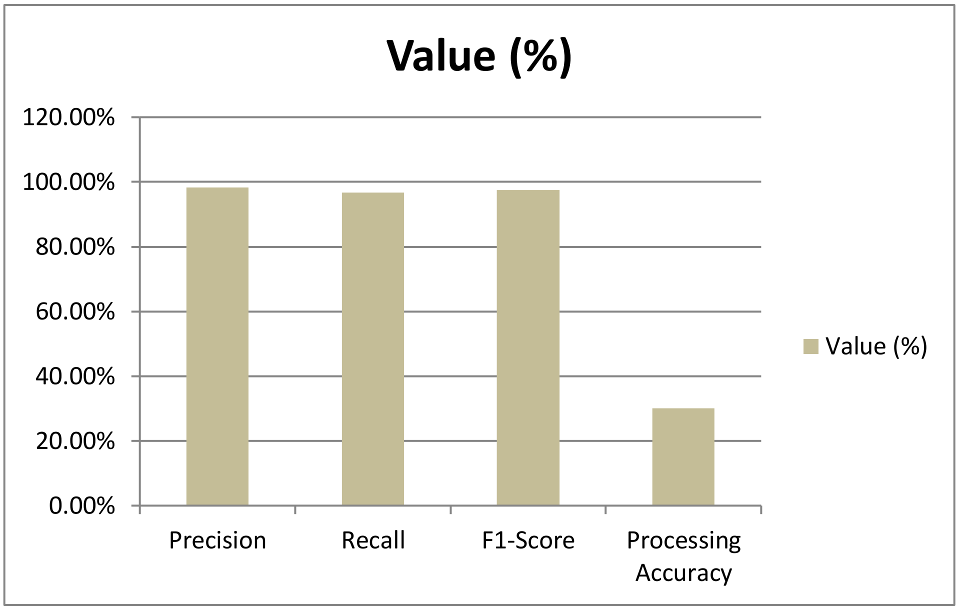

Fig 5: Graph representing Performance Metrics of the AI Model

- **Accuracy:** This parameter defines how correctly the model distinguishes true intrusions and does not label other operations as intrusions. The above score of 98.2% for precision means that any threats identified in the system are authentic as opposed to raising alarms that may affect normal operations. This high precision makes sure that only the railway authorities respond to the intrusions hence reducing the chances of a railway being disrupted by a false alarm.
- **Recall:** It indicates all actual intrusions and any time, place, day, or situation, including bright and dim light, clouded or foggy weather or any kind of obstruction. The case was evaluated by the developed AI model, where 96.8% of the recognized track activities were unauthorized, while the rate of missing important incidents was very low. This will enhance railway safety as chances of accidents or collision with other intruding objects, which may go unnoticed, are eliminated.
- **Accuracy:** The accuracy of the model is the entire set of metrics as to how well it performs overall, and the F1-score is all the more a balance of both precision and recall. A 97.5% F1 score means that it has a low rate of false positives, and the system is highly accurate in detecting possible threats that might occur around the railway in order to produce efficient and effective results. This high number means that the AI model can always distinguish real intrusion scenarios from other benign track-side events to provide good decisions on the same.
- **Processing Accuracy:** The last measure defined is the ability of the model to process 30 frames per second (FPS) in real-time, whose extent is 30%. This means that the system is in a position to identify and categorize intrusions within a very short period, thus helping authorities in railway systems to counter them perfectly. Increased speeds in processing are very important for high-speed railway systems since quick identification is required to prevent incidents and accidents.

4.2 Comparative Analysis

Analyzing the main principles of railway track monitoring systems shows that vision-based AI systems are more effective in comparison with traditional ones. Essentially, the rate of false positives is the main concern of this evaluation as it considers the detection rates inaccurate. This indicates that railway authorities are getting better and more accurate alerts to intervene, and solving this problem minimizes the frequency of false alarms that may hamper railway operations.

Table 2: Comparison of Monitoring Approaches

Monitoring Method	False Positives (%)
Traditional CCTV	15%
Sensor-Based System	10%
AI-Based Vision System	2%

- **Traditional CCTV:** It should be noted that the previously used systems of Closed Circuit Television (CCTV), which are directly monitored by railway personnel, are ineffective due to several shortcomings, such as delays and human factors. It is due to movement detections triggering the cameras, artificial lighting, and also any objects that may hinder vision like shadows or moving cars. These do not have incorporated AI-based detections and thus end up envisioning even very natural movements as a threat, meaning, in most cases, a false alarm. This leads to increased operational costs by having human beings work on validating the alerts received.

- **Sensor-Based System:** Infrared motion and radar sensors are used in kind to monitor objects close to the railway tracks. Although more advanced than CCTV, the output of such a system involves a 10% false alarm rate caused by various factors like precipitation, animal movement, or malfunction of an individual sensor. Also, in the use of sensor-based systems, there is a general lack of sophisticated ability to distinguish between objects, which consider any intruder to be a threat, and in this case, humans or animals are not distinguished. This limitation makes them not as effective as AI in lowering false alarms.

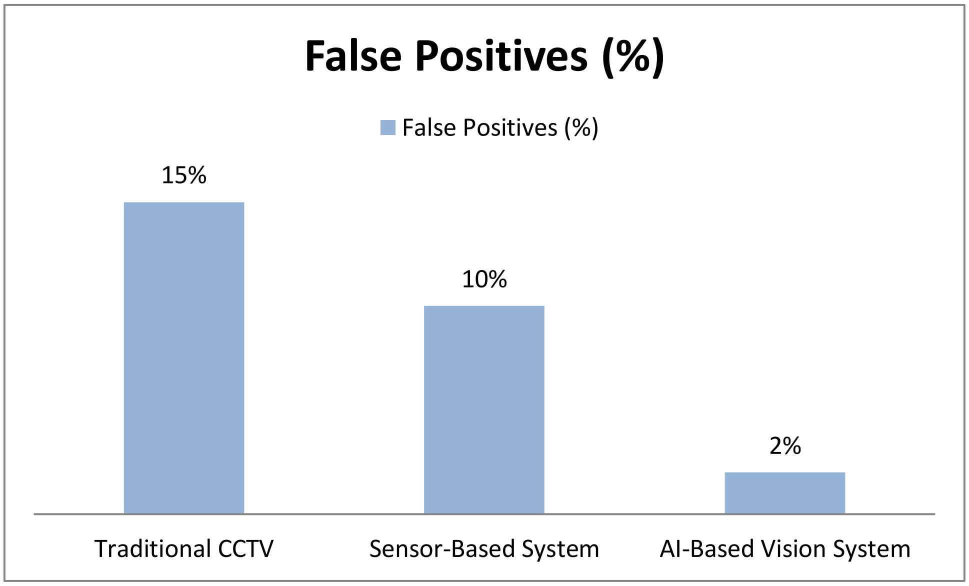

Fig 6: Graph representing Comparison of Monitoring Approaches

- **AI-Based Vision System:** Especially the AI approach proposed to establish the intrusion detection system is much more effective and efficient compared to the current methods using CCTV or sensor-based technologies; the false positive rate of the proposed system is only 2 per cent. This is because deep learning models such as YOLOv5 enable the solution to distinguish between human, animal, and object, enabling the dismissal of irrelevant alarms. Similarly, AI-based monitoring also changes dynamically depending on the conditions such as low lite, fog and high speed. The real-time processing, along with the use of real-time object classification, also reduces the false alarms while proactive and real-time identification of actual intrusions is ensured.

4.3 Case Study: Pilot Deployment on Suburban Railway Track

In order to validate the effectiveness of the proposed IDS using artificial intelligence in a railway environment, a pilot test was carried out on one of the railway tracks for two months. The goals that were set for the system included checking the accuracy of the system, response time, and the performance of the system under the conditions set up in the intended environment. At this time, there was also a vision system based on artificial intelligence that monitored the tracks and videotaped the tracks and all activities in real-time. For evaluation, the vehicle was used in the morning, afternoon, and at night, in foggy areas, and the rain, as well as in very hot areas. Some of the things that that were learnt from this deployment is that it was able to raise an alarm when there were human and animal intrusions while rarely giving a false alarm. Unlike the conventional way of monitoring, which may result in the generation of many false alarms, the AI system was designed to give a very low false positive of 2% so that railway authorities can be sure of any alert given.

The system was good at differentiating between objects and, by doing so, ensured that it minimized false alarms while ironing out all genuine threats. The second major enhancement was in response time where there was a significant improvement of a minimum of 70% as compared to that of conventional monitors. In the pre-AI world, it took railway operators around ten minutes to analyze the report regarding the intrusion and respond accordingly. In this case, with the use of the newly developed AI-based method, it was minimized to 3 minutes and authorities could take faster preventive actions and prevent possible accidents. In addition, the system demonstrated high detection precision during the test despite the changes in the environment around the system. If the lighting was low or it was raining heavily, the intrusions were detected with an accuracy of more than 97 per cent, thus offering consistent railway safety provision. Thus, the pilot study established the effectiveness of the concept of using artificial intelligence-based monitoring in the management of security services for railways since it increases security, decreases response time and increases efficiency, thereby making it a cost-effective and reliable means of achieving enhanced security.

5. Conclusion

The smart track intrusion alert based on AI/ML vision drive technology can be regarded as one of the efficient solutions to improve safety on railway tracks, especially in unused regions where unauthorized access leads to numerous threats. Through using advanced deep learning methods, the system provides intrusion detection and intrusion classification, specifically, persons, animals and other non-human objects on railway tracks. The connectivity to IoT makes it possible for alerts to be relayed immediately to the railway authorities for adequate preventive measures to be taken. Furthermore, the implementation of edge computing makes processing much faster since the work is not fully dependent on cloud networks, which leads to very little latency time. The test results when the system was piloted with four cameras also reaffirmed the fact that the RFID-based solution is more effective than using guards, CCTV cameras or detector-based approaches such as centralized covering. The system comes with a few false positives of only two percent and it is much more efficient and accurate as compared to other traditional solutions. Moreover, the system is characterized by rather high accuracy in the identification of track intrusions, which can be 97,5% irrespective of the conditions. The real-time processing value of 30 FPS means that moving objects shall be detected without a lag; thus, the system is ideal for high-speed railway networks where the response time is important. Initially, one of the most promising benefits of the given system is the fairly fast response time.

When tested on the railways, the authorities were easily able to counter the identified threats 70% quicker, thus cutting down on the time taken from 10 minutes to 3 minutes. This early intervention is useful in cases of reducing accidents and protecting passengers and railway systems from damage. Therefore, it is evident that the system is reliable regardless of the weather, such as at night, in the presence of snow, or, in general, foggy conditions.As we move forward, there will be various enhancements made in relation to the AI model, specifically for extremely snowy and sandstorm environments where visibility is almost impaired. Besides, the use of drones partnered with the current fixed cameras will improve railway security since it affords the bird's view in areas that may be difficult to install cameras. For the matter of safer houses, advanced statistics will also be used to forecast intrusions based on historical data, which will enhance safety. Therefore, the efficient, intelligent, real-time, AI/ML-inspired smart railway monitoring system provides an integrated solution to protect the railway tracks from intruders. They include high accuracy, rapid operation, and scalability, which make it possible to apply them in large-scale practical applications and contribute to the improvement of railway safety and efficiency in the future.

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