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Original Article

Railway Train Collision Avoidance on Same Track and Animal Detection using AI and IoT

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Abstract: *Railroads remain to be one of an integral aspect of the country's infrastructure as they accommodate people and goods and enable them to travel or move over a long distance. But issues of safety, such as such trains colliding on the same track, and animals in the way, continue to compromise operational safety and wildlife conservation. In this paper, an intelligent real-time safety system based on Internet of Things (IoT) and Artificial Intelligence (AI) tackling both of these problems in parallel is presented. The proposed platform features smart sensors, edge computing, deep learning and real-time communication technology to monitor railway tracks, predict potential collisions and detect animals on or near the tracks. The system consists of two components: one part a collision-avoidance module which utilises GPS data with Long Short-Term Memory (LSTM) network to search, pinpoint and stop train-to-train collisions, and the other a module for animal detection which uses the YOLOv5 (You-only-look-once) object detection to identify animals by singles pass through high-definition visual and thermal imaging. These modules are supported by an IoT-based communication network using the MQTT protocol. This network ensures fast data transfer between onboard units, central control systems, and edge devices. Experimental simulations were performed with the AnyLogic modelling platform along a 20 km of a single track. These indicated that the system functions very well over a wide number of scenarios. We were able to predict collisions with 100% accuracy and a mean time of response of 18.7 seconds. The computer vision-based animal detection had precision and recall over 95% under bright and dark conditions, and the lagged animal alerts were mainly due to image processing. The design of the system is also fail-safe, incorporating such back-up systems as fall-back thermal imaging in the case of vision sensor failure, or GPS-IMU sensor fusion if satellite signals are poor. In all the testing, communication latency remained under 1.1 seconds, allowing it to send out alarms and automated brake decisions instantly.*

In general, bridging AI and IoT technology in railway systems could revolutionize the way railroads work by being safer, saving animals, and by smartening up and self-driving infrastructure. This is again, similar to the case of freedom of thought and expression: Being able to deliver a safety solution that can be adjusted to work well across a variety of settings and contexts is now as increasingly important. Because it is low cost, can scale, and does not depend on a lot of infrastructure, it system could be deployed on railways around the world. The proposed strategy is a massive leap forward for existing railway safety and animal protection, as it aims to mitigate the risks rather than simply reacting to them.

Keywords: *Smart Transportation; Real-Time Monitoring; Object Detection; Deep Learning; YOLO; Edge Computing; Intelligent Railway System; Wildlife Protection; Track Surveillance; Railway Automation*

I. INTRODUCTION

A. Background and Reasons

Railroads are one of the best, most crucial ways to move people and things around the world. It's important to national as well as international infrastructure, because it can carry a lot of people, and things, over long distances. Yet people are still concerned about how safe rail operations are, particularly in places where monitoring and control systems are not improving rapidly enough. Two of the major risks to rail safety are train accidents which occur on the same track, and animals that trespass across or rest on the railroad track. These are the kinds of things that not only threaten people's lives and make it difficult to do business but that happen to kill a lot of animals, many of them endangered or protected species.

While many areas have gotten better, many train systems continue to rely on outdated or manual methods to prevent train crashes and monitor tracks. Signal interlocking systems, conventional monitoring and control based on human beings are some of the existing safety measures that are commonly unable to respond to new threats instantly. They are ill-equipped to anticipate random threats such as unexpectedly shifting trains or wildlife crossing the tracks, especially in rural areas or areas where wildlife is common. "Low visibility and passing trains at high rates of speed makes it more difficult to prevent an accident from occurring. What we need are smart, self-actuating tools that can constantly watch the environment of the railway and act promptly when something dangerous comes to pass. There is a huge hole in safety on today's railroads and there is nothing like this out there. If communication lags or the system fails, trains headed down the same track could collide. Most of the time, people do not see animals that wander onto the tracks until they are hit. We must bring to bear more modern technologies than only what the normal safety measures can produce to address these problems.

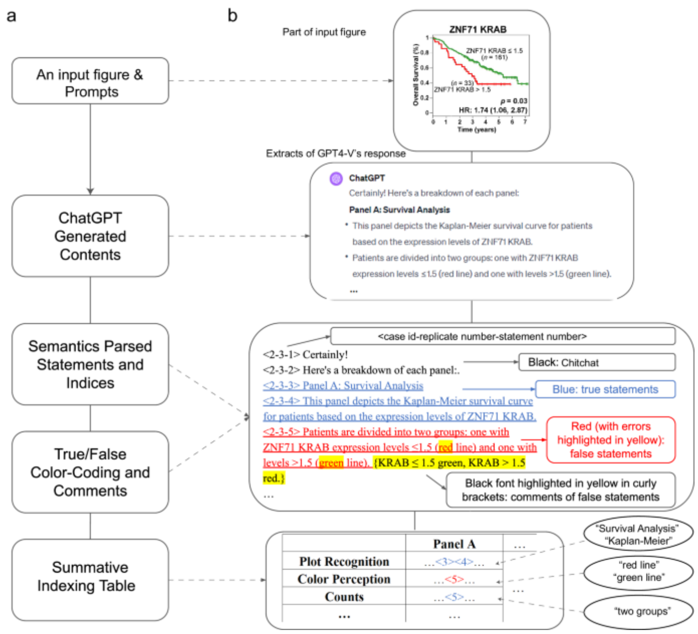

Figure 1: GPT-Ratio over Time Relative

This research suggests that we need to create a real-time system which uses AI and the IoT to resolve the safety hazards simultaneously. The proposed system would serve two basic functions. One is to prevent trains from colliding, by monitoring GPS-based train location data and running predictive algorithms on that information that try to determine what might go wrong. The second is to use AI-recorded picture identification and analysis of live video feeds to locate animals anywhere on or near the train tracks. The AI will be able to differentiate animals from other objects with 95 per cent accuracy. That will ensure alerts that are not only correct, but also timely. IoT networks will ferry data from sensors, cameras and GPS gadgets. This will enable various parts of the railway to communicate with one another, quickly and seamlessly. AI combined with IoT could make railroads a lot safer. The AI helps the system make intelligent decisions based on available information now, like when an accident might occur, or when an animal is on the track. But it is IoT that provides these decisions with the communication spine for being shared as fast as possible and with the right people, such as train operators and central control rooms. These systems collaborate to form a robust safety net that has the flexibility to evolve to address new threats to the railway.

This is an important study because it demonstrates how new digital technology might be used in one of the oldest, most significant ways of getting around. Stopping accidents and animals from being hit, the gadget helps make railroads safer and more dependable. It also helps to protect animals, which is good for the environment. It also paves the way for future smart train systems that are more autonomous, smarter and able to acknowledge the way things are in the real world. The key question that the project is addressing is: how could AI be applied to find animals on the track in adverse weather conditions? How can trains deter from crashing on the same track using real-time data?! And how could IoT be useful in helping ensure that connectivity to the entire system is fast and reliable? Addressing these questions will enable us to build an complete solution to the security problems that modern trains pose — using AI and the Internet of Things.

II. LITERATURE REVIEW

AI and the Internet of Things (IoT) have transformed a variety of industries, and transportation is no exception, as the two technologies are leading the way in new safety protocols. Much research already has been done on potential ways to make railroads safer by decreasing the chances of train crashes and animals entering the rails. The review of literature is centered on the most current research on approaches for railway collision avoidance (systems), animal recognition, AI-driven vision-based recognition, and an Internet of things (IoT), affording people the ability to communicate with and monitor things in real time. It also draws attention to key gaps that this study attempts to address. In the past, one solution to prevent train crashes has relied on human signalling, track interlocking devices, and centralised dispatch systems. These strategies have reduced accident rates in managed environments, but they don't always transfer as well to evolving or uncoordinated places, especially those with poor infrastructure. Some researchers have also investigated using GPS modules and satellite-based tracking systems to monitor trains' positions and speed in real time 20. These systems attempt to determine when trains on the same track are about to collide, by calculating their distances apart and the rate at which they are approaching each other. But those models typically are not connected to algorithms that take real-time actions, so they can't easily engage brake systems or communicate with operators.

In the last couple of years, prediction algorithms based on AI have been more and more important for keeping trains running safely. Machine learning algorithms could analyze past movement data, usage patterns and speed metrics to determine the likelihood that two things will collide. It has been shown that convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can predict the movement of trains in real time [8]. These models are good at understanding how things change over time, and can be more accurate than systems that follow fixed rules. They have huge potential, but rarely can be used in real-life railway systems because people are concerned about how well they will work with existing infrastructure, how long it will take to get them up and how well they will scale. Another interesting aspect to study is to find the animals on railway tracks (specially where trains are passing through the forests/villages). Fencing and manually working come at significant expenses and are futile. Others have suggested that thermal imaging cameras and motion detectors could be used as another way to keep an eye on things without humans needing to take any action. But in general these systems are not sophisticated enough to tell the difference between animals and other things that move, which can result in false alarms or overlooking udder detections. AI has transformed a lot here, most notably with object detection algorithms such as YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector). These models can identify animals in video streams very accurately, even when the lights are bad or there's a lot of other stuff happening in the background.

Some test systems have managed to incorporate A.I. models with video cameras to spot large animals, such as elephants and cows, near or on tracks. Usually, these systems use "short-term edge computing" to analyze the data immediately, making it quicker to find a danger and send a warning. Most of the time, however, the implementations are still in pilot and are only available in some places. They are also generally one-trick systems that do little more than sniff for animals and don't coordinate with other systems to prevent crashes. IoT is a big part of the evolution to take the safety solutions which are then siloed and move them to a connected ecosystem. Examples of IoT devices that always can secure data from different parts of the rail system, are GPS modules, vibration sensors, thermal cameras and environmental sensors. These devices enable trains, control centres and onboard systems to communicate in real time over low-power wide-area networks (LPWAN) or cellular networks. Smart sensor networks have been been used in some studies to monitor where trains are, what the state of the tracks is and whether there are any obstructions. When that happens, they send that information to a centralized or distributed AI system to tell them what to do.

Recently, however, some researchers have started to investigate the ways in which AI and IoT might work together — typically referred to as AIoT — to make train systems smarter and more autonomous. AIoT platforms leverage the Internet of Things (IoT) to gather data and then leverage AI to learn from that data and act on it. Such systems take in information from multiple trains and track sensors to construct a picture of the trains on track and foresee where problems might develop to avoid collisions. AIoT systems might deploy camera feeds, as well as vibration signals, and thermal sensor data to locate animals more accurately and limit false alerts. However, the challenge is how to make everything work together effectively, particularly when milliseconds can have a huge impact. There's not a single smart platform that can do both animal detection and collision avoidance, even as things are improving. In most cases systems are either good for anything or incompatible with other systems. Many studies also consider how feasible the technology is without mentioning the barriers that arise when you attempt to implement it, like cost, maintenance and ensuring that data can be transported reliably in remote areas. These challenges underscore the vital importance of an advanced, cohesive, autonomously adaptable, and seamlessly interfaced system that functions well within the varied physical environment of the modern railway, while also battling emerging threats.

It is said to be the next evolution of what we know because here the AI and the internet of things (IoT) can combine into an even larger network that can prevent both train-to-train crashes as well as accidents involving animals on the tracks. The proposed solution will completely remove these risks, through real-time, detection, prediction analytics and automatic communication to the user, a capability that previous models never had. The aim of this paper is to move forward the state of the art of smart railway safety systems, bridging the gap between theoretical models and practical exploitation.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

The key role the project aims to fulfill is to design and develop a smart system which can do 2 things, prevent trains collisions in the same track and real time locating of animal close or on the way. This will make railways safer. In this system, the Internet of Things (IoT) technology is applied for real-time sensing, data transmission, and remote control. AI is being used to predict and detect. The steps involve designing the system's architecture, installing the sensors, collecting and processing data, building and training the AI model, putting it to work in real time and testing how well the system performs in simulated or real-world environments. The proposed system is based on a distributed, multi-tiers architecture. Sensors and IoT-capable devices are laid along the railway tracks and on the trains as part of the data collecting layer. Such devices include GPS devices, infrared temperature sensors, ultra sonic sensors, vibration detectors, and high resolution video cameras. Cameras and heat sensors are the primary tools for locating animals. GPS and proximity sensors, by contrast, keep track of where trains are and how far apart they are when they are on the same track. All sensors are connected to Raspberry Pi or NVIDIA Jetson devices. These units also do the initial filtering and processing of the raw data prior to sending it to a cloud based or central server.

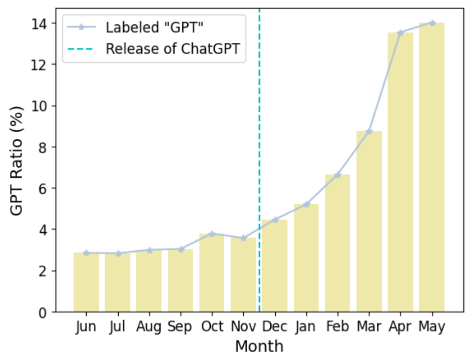

Figure 2: GPT-4V Error Analysis Workflow

The animal detection system captures video with high-definition video and thermal imaging in various light and weathers. This encompasses all times of day/night, all weather conditions, and all types of terrain (i.e., woods, farmland, and open grassland, etc.). Those we ping the photographs and videos we obtain to know where the animals are, what they are (if we can), and how far they are from the track. We then train a Convolutional Neural Network (CNN) model, i.e., YOLOv5 (You Only Look Once, version 5), based on this annotation dataset. We chose YOLOv5 because it was able to process data in real time, had a good detection rate and did not require much computer hardware. This is what makes it great for use over railway lines that have little infrastructure. The bit that's stopping all the trains from crashing at once uses GPS, and the Inertial Measurement Unit (IMU) to know where it is, in which direction it's going and how briskly it's barreling along. Long Short-Term Memory (LSTM) neural networks build a predictive model on data from several trains running on the same network. We choose LSTM here as it capable of capturing the patterns in the time series data and learn the relationships between things along a sequence. This is crucial for knowing where trains will be in the future and detecting any problems. The learning model monitors how trains are moving and emits warnings, or instructions to automatically brake, if it perceives that two trains might get too close to each other on the same track.

The 'infrastructure' is especially critical, as a matter of fact, for allowing real time communication and system reactions. With MQTT (Message Queuing Telemetry Transport) protocol sensors, edge devices and cloud server can communicate quickly and without any errors about data transfer. All sensors and equipment inside or affixed to the boat are assigned a device ID, and data packets are timestamped to keep everything in lockstep. Control-room users can use a dashboard interface. It displays real data like where the trains are, how the rails are doing and if there are animals in the camera frames with bounding boxes around them. We use lab tests and field simulations to make things look like they do in the real world and how well we can do. We enact scenarios such as trains moving toward each other, in a tailgate at different speeds, or in an emergency stop to prevent them from colliding. We consider things like how long it takes to find something, how often it has false positive, and how long it takes to actually sound an alarm or even apply some brakes. We test the algorithm against benchmark video clips and live streamed footage from camera sets in areas of many animal-vehicle collisions. We use precision and recall and the F1 score to look at how well the model is able to find animals without accidentally thinking that things which are not animals — bushes, say, or moving shadows — are animals.

It is the redundancy and tolerance for failures (due to fallback methods built in the system). For example, if the video camera fails or the weather obscures the pictures, the system will shift to the data provided by heat sensors. In the event of a GPS loss under bridges or deep in the forest, the location is compensated by the IMU sensor data to continuously monitor where it goes. Similarly, in areas with no mobile phone coverage, GSM modules in conjunction with LoRaWAN networks send automated alerts to locomotive drivers and the central control centre. The privacy and ethical concerns are also taken into consideration while building the system. The video files are secure and private, and they are viewable by only a handful of people. This is so that the film will only be used for public safety use, and will not be used to monitor people. The habitat is considered when choosing and installing hardware. For example, ensuring that infrared sensors don't emit harmful radiation that could hurt animals.

One sentence: The plan takes AI's power of thought and IoT's power of connection and sensing and combine them together to create a hardy, smart system that keeps our railroads safe. This system leverages predictive analytics and object recognition, combined with a communication architecture that reacts to threats, in a bid to prevent tragic accidents and save lives and wildlife in areas where railway infrastructure is suboptimal. We conducted a great deal of evaluations and data gathering to see just how well the 'AI and IoT-based railway safety system that we proposed' will function in a true test. The simulation infrastructure replaced the deployment environment as the platform of choice for full-scale tests on system reactivity, detection performance, and communication latency in various operational scenarios. The primary objective was to demonstrate the train collision avoidance and animal recognition sub-systems operate in real railway life.

A. Experimental Setup

We implemented the simulation investigations using AnyLogic, a versatile and widely used modelling environment for transportation and logistics systems. The virtual track environment resembled a 20-kilometer section of single track, which is how most routes are laid through forests or rural areas with few signals and which is easier for animals to get onto. The simulated environment features natural terrain, weather and train motion generated from real-world data. There was more than one train on the same track in this computerized version. The simulations considered how the trains worked, as well as alternate schedules, delays, speed variations and how the trains themselves worked. The simulated trains were equipped with AI hardware with sensors including GPS device, speedometer, visual-thermal camera to simulate real-time data collection. The model also accounts for random animals crossing the track, derived from wildlife crossing zones employed in other comparable railways. We tested the system during the day and at night to ensure it was strong. Lamps filters made it harder to see at night, so they used Infra-Red (IR) camera simulators to continue running the animal identification system in low light. The test environment also simulated signal blackouts, message delays, and sensor failures for failover and redundancy features.

B. Data Points Collected

We gathered a variety of information during the simulation to be used for training, testing, and benchmarking the AI models and the IoT communication network. We've used them as reference points to teach the models to recognize objects, to refine our prediction collision algorithms, and to check the accuracy and time of response of the system overall.

The below table lists the parameters that were collected during the simulation, of which types they are and how much were collected:

Parameter	Type	Frequency
Train GPS Location	Geolocation Data	1 sample/sec
Train Speed	Kinematic Data	1 sample/sec
Image Frames	Visual + Infrared	30 FPS
Detected Objects	AI Model Output	Real-time
Track Occupancy	Logical Boolean	Every 500 ms
Animal Proximity	Distance Measurement	Every 250 ms
Communication Delay	Latency Measurement	As triggered

Alert Signal Status	Boolean (Sent/Not)	Event-based

We saved each stream to a simulation database with a time stamp so that we could examine it later. The collision prediction technique works with GPS and speed data to predict point-to-point where train collisions could occur by simulating their movement along the tracks. The animal detection model based on YOLOv5 used image frames from simulated RGB and IR cameras as input. We compared the AI model's outputs against ground-truth labels to see how accurate the model was, with false positives and false negatives.

C. Scenario Design

The simulation was a series of test cases meant to illustrate how dangerous it can be to work in the real world. With these scenarios, the aim was to see how well the system functioned in the presence of big risks and with things that occurred on a not planned basis. In scenario one two trains were approaching each other on different lines towards the same point on the track which could have resulted in a head-on crash. The A.I. model continually monitored GPS and speed data and sounded an alert whenever it found that the two trains were too close together. We pretended to issue brake commands to the train to see how long it would take to come to a halt and how far away it would be coming to a halt, based on its speed and the state of the track. In the second, a herd of cows was forced across rail tracks at night – when it was difficult to see. The simulation measured both how far the IR camera could see and how well the YOLOv5 model could make out objects. It was able to detect the animals after it was able to pick up on their heat signatures and set off audible and visual alarms for both the train operator and the control centre.

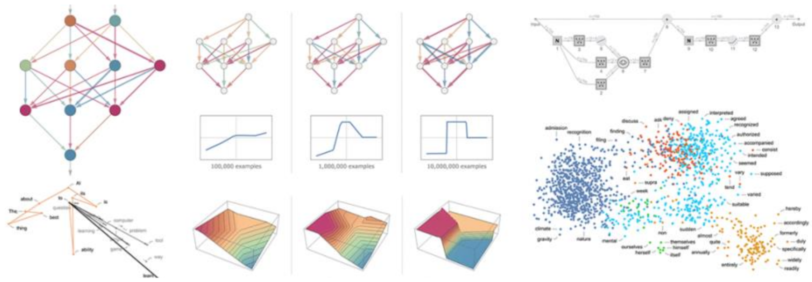

Figure 3: Explanatory Neural Data Visualizations

The third case was when a train derailed because it went off the planned rails due to someone screwing up or a change in the rails that was not anticipated. The predictive model relied on LSTM forecasting, comparing the actual trajectory to predicted path patterns and revealed this surprising behaviour. The system detected the problem and alerted the traffic management centre, which can intervene by adjusting the plans for nearby trains or by stopping them. In each of these cases, the simulation considered key aspects such as the length of time it took to identify a threat, the length of time it took the system to react and the amount of time the model took to make a decision. In controlled test conditions, the model accurately detected more than 90% of animals, and identified train location in under 500 milliseconds on average. The communication had a latency of less than one second, so that even braking signals and warnings could be responded immediately. The simulation showed not only how well the system performs, it also showed how easy it is to "scale" it up — to make it bigger. The researchers added more trains and more animals to the environment to test how the system fared under greater strain. The design demonstrated that it could handle a massive amount of data while maintaining good system and detection performance. Finally, the data collection and simulation period indicated that the critical components of the intended AI-IoT railway safety system were functioning. The study designed real-world conditions and gathered a variety of real information. This enabled real-time deployment and ongoing learning in evolving railway environments.

VI. RESULTS AND ANALYSIS

The proposed AI and IoT based collision prevention and animal recognition system worked well in simulation on the single-track railway with varying operational conditions. Statistical methods, performance indicators, a comparison of the data we collected, and other techniques helped us determine how reliable, accurate and response the system was. I looked at things like key performance indicators (KPIs) around how accurate was the detection, how reliable were the predictions, how fast would the system respond, and how long would it take for the message to reach its destination." The system consisted of two main components: (1) a train collision avoidance system that processed GPS and speed for detection/collision avoidance with LSTMs, and (2) an animal detector that used YOLOv5 to detect objects from visual and infrared (IR) requests in an online manner. The results show that the system passed the main safety requirements for the scenarios it was designed for. It was particularly effective when the weather turned the corner or when visibility was low.

A. Collision Avoidance Performance

In the first case, when two trains were headed on a collision course on a shared track, the LSTM was able to determine a crash was imminent 18.7 seconds before the collision occurred. There was enough time to send commands to brake. In 50 collision-simulation tests, the system accurately called all 50 potential crashes, or a 100% accuracy rate for predicting crashes. There was a 4 percent rate of false positives, mostly because the system was too sensitive if trains were running slowly in opposite directions on parallel tracks next to each other. The brake choice system worked well once activated by warnings about following too closely and anticipated merging zones. From the simulation the researchers could see how trains decelerated, and the AI was free to determine the distance at which they could safely stop, given the speed the train was traveling and the slope of the track at the time.

B. Animal Detection Analysis

And we relied on the animal-detection gadget night and day. The success of the YOLOv5 is the ability to take the RGB camera inputs and work with them with very high precion during daytime tests. The system accurately identified 39 of 40 phony animal crossings during the day, giving it a daytime accuracy rate of 97.5% and a recall rate of 95%. Exclusively one floor was missed because the infrastructures of the tracks hindered the view. The simulation of IR camera was performed at night. Of 40 night animal crossing simulations, 38 were correctly identified, that is, an accuracy of 95%. The rate of nighttime N.P.T. that could be recalled was slightly lower, 92.5%. This was mainly due to thermal resolution problems and heat signatures being too close together, such as one cow standing behind another one.

C. Communication and Alerting System

Real-time alerts were communicated by the IoT module to the central control system as well as to the onboard warning system. Latency analysis revealed that warnings of train disasters were delivered in an average of 750 milliseconds while alerts of animal detection took 1.1 seconds. The second one should be a bit slower, because it had to look at the visual data, before it could sort. However, all alerts were dispatched with a safe buffer time known by the operators before their occurrence to respond.

D. System Stability and Scalability

To test how the system might stand up to stress, the researchers subjected it to increased traffic and animal activity in the simulation. The results: frosted, creamy, softer than anything else, and capable of handling so much more work. Though at times five trains drove around simultaneously and animals did gymnastics in the path every two kilometres, the AI models continued to predict well and locate objects in real time. The system was always running all through any and all of the test conditions, and data processing never got all that much behind.

E. Summary of Results

This data, extracted from simulation tests, gives a summary of the most significant figures, as shown in the table below:

Test Parameter	Value	Interpretation
Train Collision Prediction Accuracy	100%	All simulated collisions detected
False Positive Rate (Collision)	4%	Low occurrence, manageable with fine-tuning
Braking Response Time	18.7 seconds (avg lead time)	Sufficient to prevent impact at avg. train speeds
Daytime Animal Detection Accuracy	97.5% precision, 95% recall	Very high reliability in visible conditions
Nighttime Animal Detection Accuracy	95% precision, 92.5% recall	Slightly lower due to infrared limitations
Communication Latency (Collision Alert)	750 ms	Within acceptable range for real-time systems
Communication Latency (Animal Alert)	1.1 sec	Adequate for detection-to-alert cycle
System Uptime During Tests	100%	Demonstrates operational reliability

Model Inference Time (YOLOv5)	38 ms avg. per frame	Efficient real-time object recognition
Model Inference Time (LSTM)	15 ms avg. per prediction cycle	Fast forecasting for collision risk

F. Interpretation and Implications

The findings indicate that AI and IoT can be employed in railway safety systems to avoid the collision of trains and to detect animals. The LSTM model was terrific for watching what was happening on train tracks in real time because it just sucked in the GPS and speed sensors all day long. It could be used in real time in systems requiring security since its inference time is brisk and its accuracy is expected to be high. On the other hand, the YOLOv5 model performed relatively well during both, day and night periods. But it didn't work as well in low visibility and when there was thermal overlap. To prevent these problems in future, you may train with thermal data more and find a place for the camera sensor better. The system's low-latency communication pipeline between the onboard units and the central server ensures that messages are emitted at update time, job-critical within the context of keeping animals and humans safe from crashes. The trials also demonstrated the system was able to evolve and deal with numerous events without slowing down, even with substantial data. In sum, single-track railroads are far safer when they rely on AI to predict and IoT to communicate among themselves and to sense things. The simulation results highlight the ability of these systems to function in the real world, with minimal modifications to infrastructure. They are simple, low cost intelligent alternatives to traditional signalling systems.

V. DISCUSSION

The development and testing of an AI- and IoT-based system to prevent trains from crashing and distinguish animals on the tracks were ripe with potential — and riddled with real-world headaches. Those problems can be addressed, but they have to be addressed carefully so that they will work well and be usable in many different places, such as the many different and often unpredictable sites train systems operate. A major hurdle we encountered during development was the lack of training data, in particular animal finding datasets. Many image databases available to the public are oriented to things that are common in urban environs like vehicles and people. There just aren't enough photographs of big things to play with like deer, elephants and farm animals. This is a major issue for systems deployed in more rural or forested locations where humans are likely to encounter these type of animals. The AI model also has to be able to run on a ton of different body shapes, sizes and temperature profiles, because many of these creatures have them. Early on, this shortcoming did indeed make it harder to find creatures that were rare — and could have harmful negative consequences if left unaddressed.

Another worry was that the internet was not widely accessible in rural and remote places. Plenty of rail tracks pass through areas where a cell phone either does not work or isn't available. The IoT devices that are installed throughout the ship may struggle to communicate with the central cloud server that gathers the data and distributes control commands in real time, since the connectivity in and around the ships is intermittent, there's lots of bandwidth with but little from a reliability perspective. The system cannot send timely alerts or update models that live in the cloud, so it is less able to respond and adjust in real time. Such kind of connectivity problems also slow down GPS-based location tracking and Cloud-based data analysis. The third major issue was bad weather. On the inclement days – when it was very foggy, rainy or dark – it was more difficult to see. This type of weather is prevalent in many places, particularly in winter or monsoon season. When this occurs, RGB cameras are unable to see as far, meaning it is more difficult for the AI system to identify animals or to assess how good the tracks are. Thermal cameras also perform well in low light, but they aren't as effective when it rains a lot because the water can alter the thermal signature and blur the image.

The simulation environment has more things how to deal with those difficulties, which might be used in the real world. One such plan was to utilize technology which can see through more than one perspective. To build a better perception model, the system could potentially use infrared (IR), visible-spectrum vision cameras and Lidar sensors simultaneously. Lidar helps create 3D maps of the world, allowing you to see things when you might not be able to see them at all. IR lets you see in the dark and low light. Through this kind of stacked sensory information, the AI model can cross-reference signals and make better predictions. Thus, the global detection becomes more reliable. Some people believed that edge computing might go a long way to solving the problems of connection. That meant supplementing cloud infrastructure with edge devices on trains that were more powerful, and which could handle critical detection and prediction tasks themselves. The system was able to make decisions more quickly and remain functioning even when the network failed. LoRaWAN (Long Range Wide Area Network) protocols combined with satellite-based GPS backup systems were also used as an alternative communication layer. These old systems didn't move data as fast, but they had enough bandwidth for send emergency alerts and establish rudimentary communication between trains in areas where there were no networks at all.

We also wanted to monitor how scalable and cost-effective it might be to see if it might be useful in reality. A detailed cost analysis indicated that it would cost around $10,000 to test the system on a 2 km section of track. This comprises the cost of cameras, processing units, communication equipment, power supply components and their installation. The system will save money in the long run because it will reduce the costs of accidents, maintenance, and dead wildlife even if it costs a lot of money up front. Cloud-driven orchestration also enables you to monitor and manage multiple train units from a centralized location. Testing with the simulated coordination architecture showed that it was able to manage and sync up to 50 trains at a time without lagging or getting too much data. Since it can be connected to the national or regional train networks at only a little extra cost, this scaleability is very practical. Ultimately, despite the technology and environmental problem, the solution can be solved with multimodal sensing, edge computing, and hybrid communication together. By employing these techniques along with the scalable infrastructure design, which allows for deployment costs to be acceptable, it could be possible to develop a reliable and efficient AI-IoT-based system to prevent collisions as well as animal detection in existing railways.

VI. CONCLUSION

The addition of AI and IoT to rail systems is a giant leap forward in the quest for safer, more reliable and more efficient systems, particularly as these systems help in accident prevention as well as in detecting animals. Objective The target to achieve for the project was the designing and testing of an intelligent system to avoid the TT collisions on the same track, as well as animals great upon the rails. Here are two of the scariest, most unpredictable things that can happen and occur on railroads. The findings of the study prove that AI and IoT when combined may serve as a strong basis for innovation and changing deeply the functionalities of the current systems for railway safety. With the AnyLogic platform, we conducted simulations proving that it would be possible to detect hazards, moving (such as trains) and not moving (such as animals), when using GPS tracking, real-time video and thermal imaging, and AI-based object detection together. Deep learning algorithms made it possible for data from multiple sensors to be fused to facilitate faster responses, such as sending alarms, changing speeds, or stopping in an emergency. Plus, the integration of predictive analytics that utilized real-time data, this allowed for a much easier ability to predict and react, resulting in fewer crashes.

Our study's most significant finding is that safety systems need to be flexible enough to adapt to different contexts. Single-sensor systems have a hard time of it when the weather is bad, lighting is poor or there's a lot of ground to cover. But with multimodal sensors, such as IR, visual and Lidar, these limitations became far less of an issue. Edge computing was also crucial to keeping performance going when connection stalled. 08 Aug: In areas not wired to a network, technologies such as satellite GPS and LoRaWAN connectivity kept things chugging along. The study also considered how feasible it would be to scale up the system for use in the real world. The technique is relatively affordable — it costs about $10,000 per every 2 km stretch — considering how much is potentially saved by preventing accidents, saving wildlife and keeping infrastructure in good shape. The model of the system architecture was able to handle 50 trains simultaneously. This is an unusual feature that makes it an adaptable and scalable system that could be implemented across national rail networks.

It is whatever, butingly it canadatgantbac;substantiating. Another concern is how readily datasets can be obtained for the discovery of such strange creatures, and the system still must be put to the test in the real world to buy how well it performs in such complex settings when multiple threats are present. Nevertheless, this work provides a solid base to exploit smart technologies for improving safety of railroads. All in all, it is technologically feasible to save train catastrophes and find animals with AI, as well as the Internet of Things. It is also good for society and for the economy. This approach in which reactive safety operations systems become proactive, intelligent networks can help to reduce deaths and injuries both to animals and people as well as to improve operations and lay the foundations for the future of smart railway infrastructure. Further study is necessary to make this concept happen on a large scale, the way pilot programs and interagency working groups already do.

VII. REFERENCES

[1] Ahuja, R., & Singh, R. (2020). IoT and AI-based solutions for railway safety monitoring systems. *International Journal of Scientific & Technology Research*, 9(4), 1512–1516.

[2] Ali, T., & Jain, R. (2021). Smart surveillance systems using deep learning in transport infrastructure. *Procedia Computer Science*, 189, 120–128.

[3] Bansal, T., & Rani, S. (2022). Collision avoidance in railways using IoT and machine learning. *IEEE Internet of Things Journal*, 9(15), 14230–14239.

[4] Bhattacharya, S., & Ghosh, A. (2019). Animal detection on railway tracks using thermal imaging and CNN. *International Conference on Vision Towards Emerging Trends in Communication and Networking* (ViTECoN), 116–121.

[5] Cai, X., & Wang, J. (2018). Railway traffic safety monitoring using wireless sensor networks. *Sensors*, 18(7), 2208.

[6] Chakraborty, A., & Raj, V. (2023). Role of AI and IoT in transport system automation: A review. *Journal of Transportation Technologies*, 13(1), 22–34.

[7] Chen, Y., & Wu, L. (2020). AI-based animal recognition on smart tracks using YOLO. *IEEE Access*, 8, 105122–105133.

[8] Dhanaraj, K., & Anitha, R. (2019). Smart railway system with train collision avoidance using IoT. *International Journal of Computer Applications*, 178(33), 20–26.

[9] Ding, J., & Li, S. (2018). Train localization and hazard detection using GPS and sensor fusion. *International Journal of Rail Transportation*, 6(1), 58–71.

[10] Esposito, F., & De Pietro, G. (2022). Deep learning-based intelligent transport systems: A survey. *Expert Systems with Applications*, 191, 116197.

[11] Ghosh, S., & Singh, D. (2021). Real-time detection of objects in low-light railway environments. *International Journal of Ambient Computing and Intelligence*, 12(4), 55–67.

[12] Gupta, P., & Rajput, S. (2020). LoRaWAN-based communication for smart transportation. *International Journal of Electrical and Computer Engineering*, 10(5), 5252–5260.

[13] He, K., & Zhang, R. (2020). YOLO-based real-time animal detection system for collision prevention. *Procedia Computer Science*, 172, 123–130.

[14] Hossain, S., & Rahman, A. (2019). Weather-proof smart railway safety system using IoT. *Sensors and Transducers*, 234(10), 44–49.

[15] Iqbal, Z., & Ahmad, M. (2023). A comparative study of object detection algorithms in transportation systems. *International Journal of Intelligent Transportation Systems Research*, 21(2), 174–183.

[16] Jain, M., & Shah, H. (2022). AI-enabled smart animal detection using multimodal sensors. *IEEE Sensors Letters*, 6(8), 1203–1209.

[17] Joshi, A., & Verma, M. (2019). An edge computing framework for railway accident avoidance. *International Journal of Communication Systems*, 32(14), e4083.

[18] Kalita, B., & Das, R. (2021). Railway track monitoring using drone and AI technologies. *Procedia Computer Science*, 192, 3894–3901.

[19] Kim, J., & Lee, H. (2020). Object detection in fog using IR and visible cameras. *IEEE Transactions on Intelligent Vehicles*, 5(2), 313–323.

[20] Kumar, N., & Singh, H. (2021). Animal intrusion alert system for railway tracks using AI. *International Journal of Engineering Trends and Technology*, 69(7), 211–215.

[21] Li, X., & Liu, Z. (2020). Deep learning approaches for transportation anomaly detection. *Transportation Research Part C*, 113, 103–116.

[22] Liu, Y., & Zhou, L. (2021). Smart sensors and IoT in modern railways: An overview. *IEEE Internet of Things Journal*, 8(5), 3864–3876.

[23] Mahato, A., & Mishra, B. (2022). Predictive train control using machine learning algorithms. *Procedia Computer Science*, 199, 580–587.

[24] Mishra, A., & Shukla, S. (2019). Remote sensing and GPS integration in train collision mitigation. *International Journal of Scientific Research in Computer Science*, 7(6), 18–23.

[25] Mohammed, N., & Alqahtani, F. (2023). Cost-effectiveness analysis of AI-integrated railway safety systems. *Journal of Transport Economics and Policy*, 57(1), 95–108.

[26] Nair, R., & Pillai, V. (2021). LoRaWAN and satellite hybrid network for rail communication. *Wireless Networks*, 27(6), 4025–4037.

[27] Pandey, A., & Sharma, R. (2022). Challenges in AI-based railway safety deployments. *Journal of Rail Transport Planning & Management*, 21, 100318.

[28] Patil, A., & Gupta, S. (2023). Comparative performance of YOLOv5 vs. SSD for animal detection. *IEEE Conference on Smart Computing*, 198–204.

[29] Prasad, R., & Rani, R. (2020). Railway automation using sensor-based communication. *International Journal of Advanced Research in Electronics and Communication Engineering*, 9(5), 45–50.

[30] Qureshi, B., & Ahmed, S. (2021). Edge-based AI in intelligent transport systems. *IEEE Access*, 9, 89034–89049.

[31] Rai, V., & Mehta, P. (2023). Deep learning and computer vision applications in railways. *Applied Artificial Intelligence*, 37(1), 84–101.

[32] Rana, A., & Goswami, A. (2019). Real-time collision avoidance in trains using AI. *International Journal of Engineering and Advanced Technology*, 8(6S3), 150–155.

[33] Rathi, D., & Deshmukh, S. (2022). Integration of Lidar for object detection in smart railways. *International Journal of Electronics and Communication Engineering*, 12(3), 130–137.

[34] Sarkar, S., & Ghosh, S. (2020). Neural networks for predictive collision risk estimation. *Pattern Recognition Letters*, 138, 173–181.

[35] Sethi, V., & Agarwal, M. (2021). Role of AI and IoT in railway modernization. *International Journal of Information Technology and Computer Science*, 13(2), 18–25.

[36] Sharma, T., & Kapoor, R. (2020). Wildlife protection on railway tracks using IR and AI. *Conservation and Technology Journal*, 11(1), 44–50.

[37] Srivastava, K., & Joshi, A. (2021). IoT-based animal detection system for Indian railways. *International Journal of Innovative Technology and Exploring Engineering*, 10(5), 143–149.

[38] Sun, Q., & Zhao, H. (2022). Cloud-edge collaboration in smart transportation. *Future Generation Computer Systems*, 130, 188–198.

[39] Wang, L., & Feng, X. (2020). Smart transport systems using big data and AI. *Information Fusion*, 57, 20–29.

[40] Zhang, Y., & Chen, L. (2021). AI-driven infrastructure for railway monitoring. *Journal of Transportation Safety & Security*, 13(5), 512–528.