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Elephant Conservation on Indian Railways Using Deep Learning Techniques

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Abstract

This work proposes a novel solution to address the challenges of elephant-railway coexistence, such as the risk of collisions, habitat fragmentation, and human-elephant conflicts. The approach involves using a neural network-based monitoring system to track elephant activity near railways. The goal is to create an AI-powered surveillance system capable of real-time detection and tracking of elephants, identifying high-risk areas for collisions, mitigating human-elephant conflicts, and preserving elephant habitats. By integrating cutting-edge technology with conservation efforts, the main objective is to improve railway safety, support sustainable coexistence between elephants and railway infrastructure, and contribute to elephant conservation. The system uses YOLO with a custom dataset to detect elephants with an accuracy of 98.4%, and a custom CNN model for train detection, achieving 91.5% accuracy. With an inference speed of 150ms, the system is suitable for real-time implementation. An Alert signal is sent to the relevant higher authorities, and an infrasonic wave generator can be used to safely drive elephants away from danger zones thereby reducing accidents and conflicts.

Keywords: Elephant and Train Detection, Infrasonic Waves, Custom CNN, Elephant Conservation.

1 Introduction

Wild animals play a vital part in the human life and conservation of ecosystems. They are an integral part of nature and phenomenally impact human life. However, they are prone to various man-made threats including water poisoning through industrial activity to hunting. Animals are killed paramount in human -animal interaction through vehicles like trains etc., they are unnoticed to some extent however they pose serious concerns. Endangered animals when killed in small numbers, are prone to becoming critically endangered to extinct species. Therefore, mitigating the threat vectors with the aid of technology would serve the purpose. Animal recognition plays a vital role in addressing various challenges that impact both individuals and society, particularly in confined environments where the safety of both humans and animals is at risk Panda et al., (2022). It involves the automatic identification of animals (Villa et al., 2017; Li, 2021) based on visual or auditory features, often referred to as animal

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identification or species classification. By automating the recognition of species and individual animals, researchers can gain valuable insights into population trends, habitat use, migration patterns, and species distribution. They employ various methods to solve this problem.

Animal recognition plays a vital role in addressing various challenges that impact both individuals and society, particularly in confined environments where the safety of both humans and animals is at risk. It involves the automatic identification of animals (Ji & Zhu, 2022; Rakesh et al., 2024) based on visual or auditory features, often referred to as animal identification or species classification. Recent advancements in artificial intelligence, particularly deep learning (Ibraheam et al., 2020), have significantly improved the accuracy and efficiency of animal recognition across diverse habitats and species. Historically, animal recognition relied heavily on manual observation by qualified specialists, a process that was time-consuming, labor-intensive, and prone to errors, especially when dealing with large datasets or challenging environmental conditions. However, with the development of deep learning techniques, particularly convolutional neural networks (CNNs), computers can now autonomously learn to extract important features from raw data, such as images, sound recordings, or sensor data. One notable application of animal recognition is identifying species involved in human-wildlife conflicts (Malhotra & Iyer, 2024; Sharma et al., 2021) and implementing measures to prevent these interactions. Recent advancements in deep learning algorithms like YOLO and SSD have made animal recognition more efficient, reducing the need for human intervention and minimizing the risks associated with manual detection.

In this context, recognizing wildlife in critical areas, such as train tracks and highways, enables authorities to take timely actions to prevent accidents. By detecting when a train has passed the station and locating elephants in the danger zone, the system can activate an infrasonic generator to deter elephants from the area. This approach reduces false alarms by accurately detecting animals in conflict zones and ensuring that authorities are alerted only when necessary. Custom datasets, such as an elephant-specific dataset, are used to train models like Faster R-CNN, DETR, and YOLOv8 for efficient animal detection. Additionally, a new CNN architecture is developed for train detection using TensorFlow and a custom dataset of Indian trains. The system generates alerts and activates the infrasonic generator when a potential conflict is detected, significantly reducing the risk of elephant-train collisions.

2 Review of Related Works

Human-elephant conflict is a persistent issue, with numerous studies proposing solutions based on PIR sensors, infrasound technology, and alternative methods. Each approach has unique strengths and limitations, aiming to ensure the safety of both humans and wildlife while addressing challenges like cost, maintenance, and environmental interference BBC Earth (n.d.).

PIR sensor-based solutions focus on motion detection and animal identification. Neha Bhadwal et al., (2019); Yadav et al., (2024) utilized PIR sensors in a border surveillance system to track intrusions, though it risks harming wildlife. Giordano et al., (2018) implemented PIR sensors with ultrasound-generating devices in crop fields, but high installation costs are a drawback. Patil & Mali, (2023); Gupta & Joshi, (2025) combined PIR sensors with motion sensors and cameras to detect animals and trigger deterrent responses like lights or sounds, but false positives remain an issue. Similarly, Panda et al., (2022) integrated PIR sensors with ESP32 cameras for motion detection and real-time alerts, while Jin et al., (2011); Ilango & Ravichandran, (2023) advanced PIR-based detection with wavelet transforms, though environmental interference and delays limit their practicality.

Infrasound-based techniques capitalize on elephants' ability to communicate using low-frequency sounds. Mathur et al., (2014) developed a system with active and passive sensing nodes to generate and detect infrasonic waves for collision prevention. Various studies explored elephants' infrasonic calls, emphasizing their utility in tracking and communication, while Dabare et al., (2015) demonstrated successful tracking of these calls over short distances. Gorhum et al., (2013) proposed a ball valve siren to generate infrasound for deterring elephants, but its complexity limits scalability.

Alternative approaches explore diverse strategies. Ngama et al., (2016) used African honeybees to deter elephants effectively, though this approach is less feasible in areas with human activity. Shaffer et al., (2019); Kurian & Sultana, (2024) investigated acoustic deterrents and agricultural solutions, such as planting chamomile and citrus trees, though their effects on other species require further study. Anni & Sangaiah, (2015) highlighted the effectiveness of seismic sensors for the non-invasive tracking of elephants. Finally, Begum et al., (2020); Sindhu, (2023); and Balakrishna et al., (2021) developed an IoT and machine learning-based system for detecting and deterring animals to protect crops. The system employed devices like Raspberry Pi, ESP8266, and Pi Camera, achieving a mean average precision of 89.32% with SSD and 85.22% with R-CNN. Despite being effective the performance of the system requires further enhancement Wang et al., (2020).

Overall, while these studies present promising methods, no single solution comprehensively addresses all aspects of human-elephant conflict. A combination of these approaches, tailored to local conditions, may offer the most effective path forward. Hence a unique system is proposed here to monitor the movement of elephants and also the arrival of train to mitigate human-elephant conflicts.

3 Proposed Methodology

Elephant recognition task involves finding the presence of the elephants in the real-time video sequence and sending alert information to the authorized personnel for further actions. The flow diagram of the proposed method is shown in the figure.1

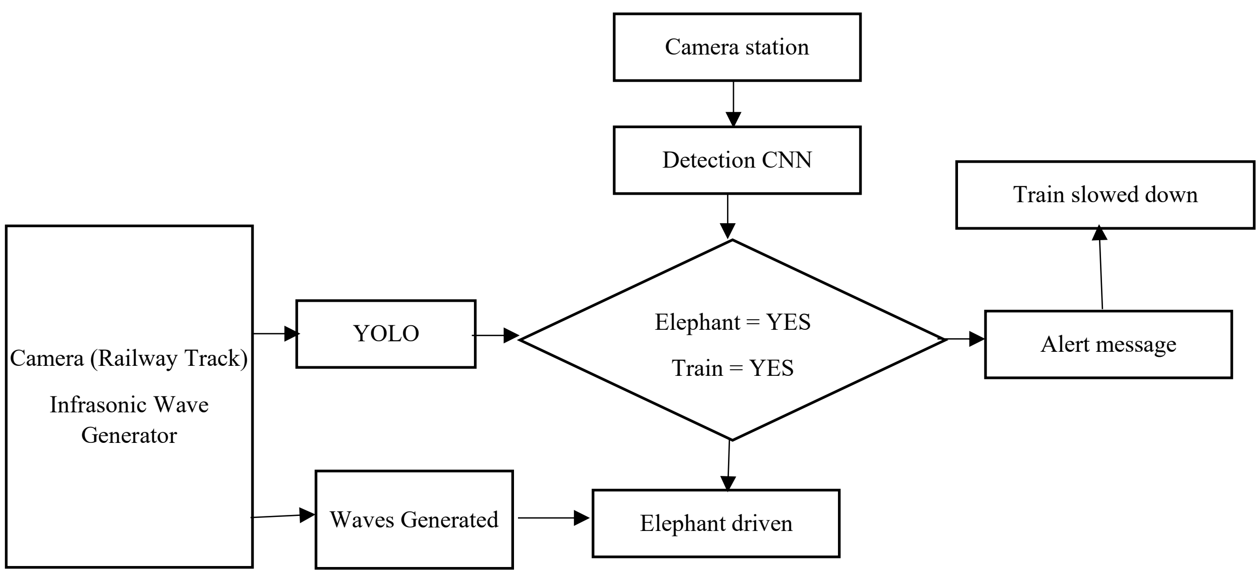

Figure 1: Flow Diagram of the Proposed System

In this system, two cameras are fixed one at the railway track to monitor the movement of elephants through the track, and the other one is located in the pole to monitor the arrival of the train. YOLO v8 is utilized to find the presence of the elephant from the captured video from the track. Once the animal is detected, then at the same time another camera mounted at the Railway station is tracked for the movement of the train towards the critical zone where the elephant is present. The time between the train crossing from the Railway station and the critical zone should be at least twenty minutes Carlos & Escobedo, (2024). The train is continuously monitored by the detection CNN through camera inputs, which also checks for the presence of elephants in the critical zone. To handle scenarios where an elephant is detected after the train has already passed the station, the system can track trains that crossed the station within the last 20 minutes. This is achieved by retrieving and analyzing the saved details from the database to ensure no trains are missed during this critical timeframe.

When an elephant is detected in the critical zone and a train has already passed the station, with a possible train identified in the database, the following two critical actions are executed to manage the situation effectively:

1. The infrasonic sound generator is triggered to emit signals that deter the elephant from the critical zone, minimizing the risk of a collision between the train and the elephant.
2. An alert is promptly sent to the loco pilot and relevant higher authorities. This allows the train crew to take necessary action, such as reducing speed, while also notifying upcoming trains about potential delays to ensure safe and coordinated operations.

3.1 Dataset

Two data sets as elephant dataset and the train dataset are utilized for this work. The elephant dataset is created to detect the presence of the elephant in the railway tracks laid in the forest zones. The dataset is created by considering the forest location, drastic environmental conditions like rain, fog, snow, etc., and lightning conditions. The elephant's data are covered from various angles. The data is gathered from open internet and around 650 images of Indian elephants are collected. Data annotation has been done in different formats required by the models for analyzing the best model out of models such as Faster R-CNN, DETR, and YOLO. All the images are labeled for the presence of an elephant in the images and bounding box coordinates are saved to the annotated file. The annotation file has to be generated for all the images to pass the image into the model for training and validation. Training images are labeled using Roboflow (Assegid & Ketema, 2023) and the number of classes and their ID are set as two. The sample images in the labeled data set are presented in the figure 2. The labels with class ID '0' represent Elephants and as 1 represents every other thing other than elephant. The images are pre-processed using techniques such as Auto-orient, resize to 640×640, Grayscale and Auto-adjust contrast. Contrast adjustment for creating greater contrast between the animal element and the background for generating perfect edges. This supports improving the accuracy of the detection process. This procedure will thereby reduce the false alarm rate and neglect unwanted stress.

The augmentation techniques such as Rotation, Exposure, Noise, Cutout and Mosaic are applied for the raw dataset. After applying all the augmentation techniques, the total number of images in the dataset is increased to 1195 images which is a considerable number for training the model for better performance. The dataset is split into a training set, validation set, and test set for experimenting with the model. Figure 3 represents the sample images of the validation dataset. The model gets trained on the training set and at the same time hyperparameters undergo modification and the model's performance continues to be monitored during the training process using the validation set and the test set is used to judge the trained model's performance on untested data. In the elephant dataset, 70% of images are used for training, 19% used for testing, and the remaining 11% utilized for validation.

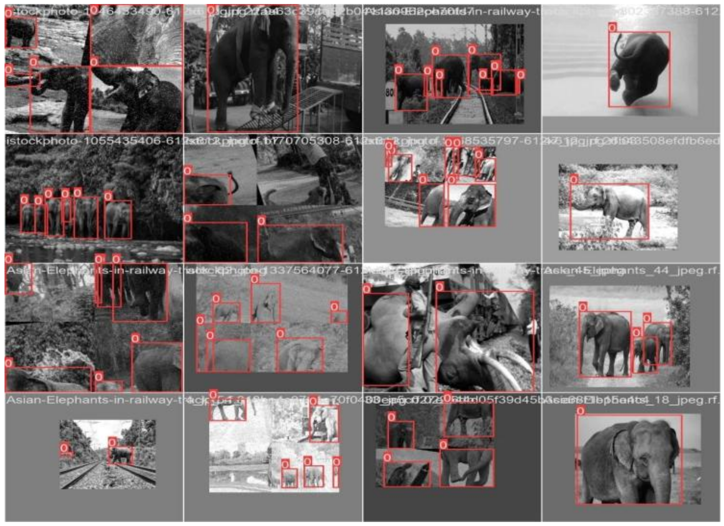

Figure 2: Sample Images of the Labeled Training Dataset

The Indian train dataset is created to detect the crossing train in the railway station near the critical zone where the elephant is detected. The dataset is created by considering the forest location of the station, drastic environmental conditions like rain, fog, snow, etc., and lightening conditions as well as in various positions. Recordings and open internet pages on the internet constitute the underlying sources of the data. The Indian Train images collected are around 200. The data gathered is annotated using the roboflow annotating tool. The annotation format required by the CNN architecture is PASCAL VOC. The XML annotation format is then converted into a .csv file. The .csv file contains the parameter index which includes filename, width, height, class, and bounding box coordinates (xmin, ymin, xmax, ymax). The value of class holds two classes as "Train" and "No Train".

Figure 3: Sample Images in the Validation Dataset

In train detection, the available data to cover all the postures of the arriving train in fast and slow motion captured by the camera is not enough. Hence in order to increase the number of images in the dataset and to make better predictions by the model, augmentation techniques Crop, Rotation, Grayscale, Blur, Noise, Cutout, and Mosaic are applied. After applying the augmentation techniques to train the dataset, there is a considerable increase in the number of images from 200 to 400. For the purpose of testing the new CNN model, the dataset is divided into training, validation, and test sets. The test set is used to evaluate the performance of the trained model on untested data, while the validation set is used to track the model's performance throughout the training process. The model is trained on the training set from scratch while hyperparameters are also modified. In the training dataset 71% of images used for training, 19% used for testing, and the remaining 10% are utilized for validation.

In Forests, the additional living things or ecological structures may partially cover animals. Furthermore, background obstacles like trees, bushes, and rocks may hamper the precision of elephant detection. This problem makes elephant detection more complex because of occlusion and background clutter. Collecting the labeled training data for elephants, especially for different behavior and various scales involving the natural environment is a very complex and expensive step. This issue can be solved by using an approach known as augmentation, which entails transforming the current data by rotation, scaling, cropping, flipping, or introducing noise. Adverse weather conditions like fog, snow and, rain affect train detection also. Hence to train the model for any adverse effects to some extent, noises are introduced as an augmentation step for the training dataset. This step also helps to stop the model from over-fitting. Data de-noising is also applied for noisy images to make the model more generalized for predicting adverse conditions.

The same dataset is analyzed and compared using the detectron framework with object detectors such as YOLO and Faster-RCNN. Using backbones such as ResNeXt{50,101,152}, ResNet{50,101,152}, Feature Pyramid Networks using {ResNet or ResNeXT} and VGG16, detectron uses methods such as Mask R-CNN, RetinaNet, Faster R-CNN, RPN, Fast R-CNN, and R- FCN. The elephant dataset is trained in Detectron with ResNet50 backbone and pre-trained in the MS-COCO dataset.

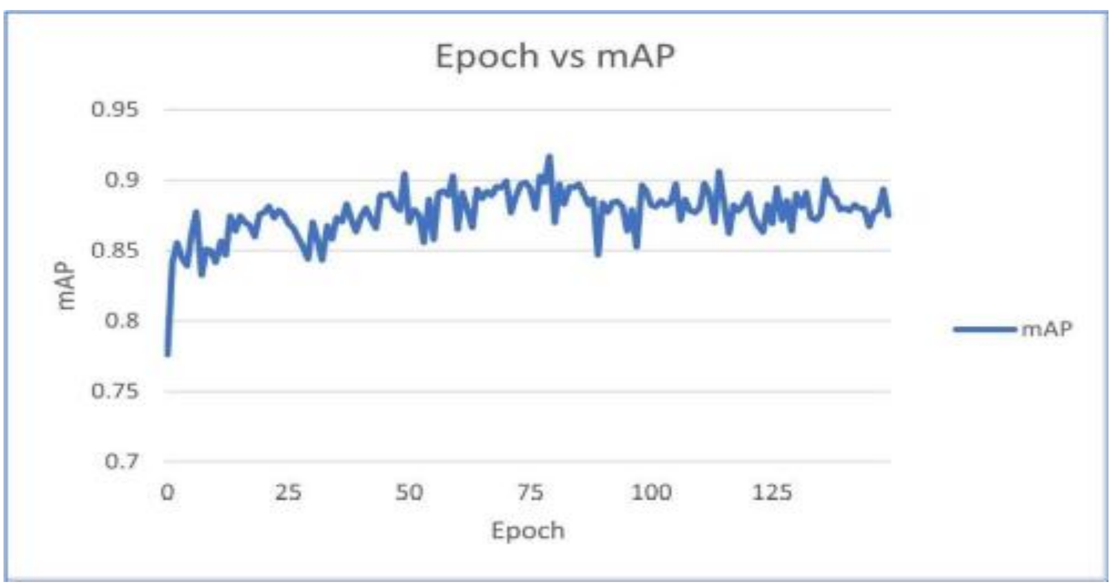

Figure 4: Epochs vs mAP

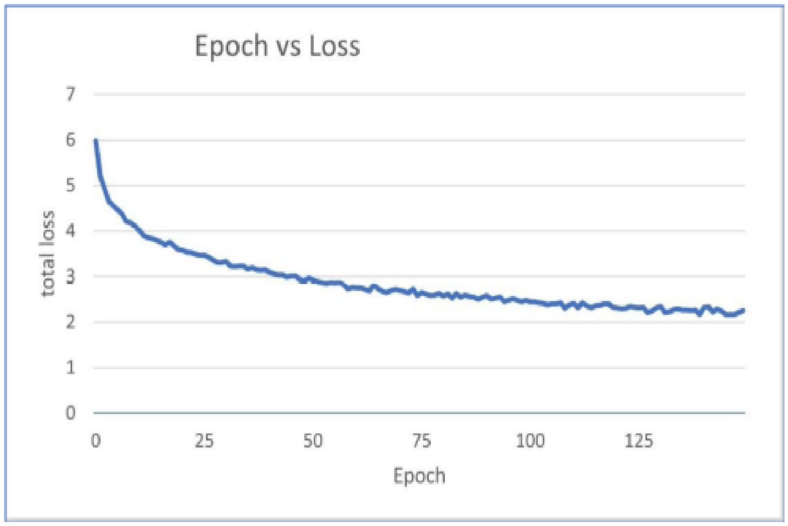

Figure 5: Epoch vs Total Loss

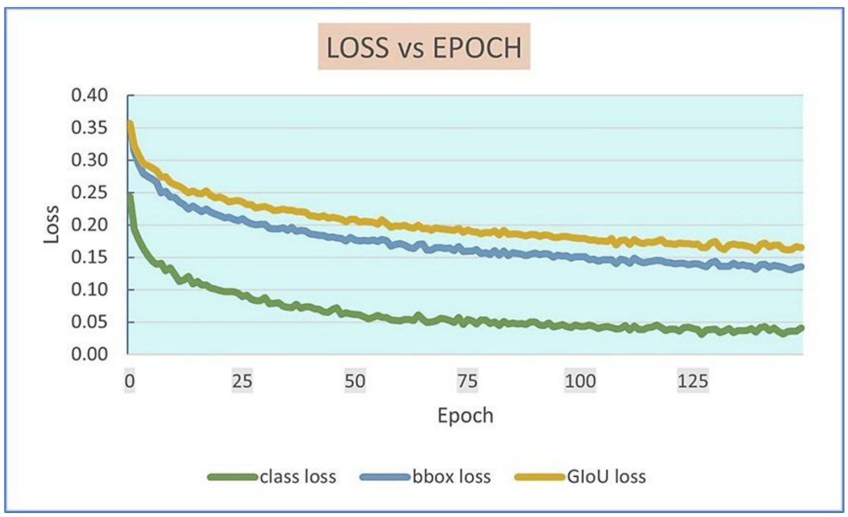

Figure 6: Epoch vs Various Losses

The mean Average Precision (mAP) is around 89.4%. As seen in figure 4, the model starts to fit in the mAP even after increasing the Epochs to 150. To know how well the model has learned the features effectively, the loss function is considered for all the epochs as shown in Figure 5. The total loss is the combination of class loss, bounding box loss or bbox loss, and gIoU loss. It starts from numerical value 6 and decreases exponentially for epoch and stays at a value around 2. This shows the features are learnt very well. The loss function is analyzed in depth in various forms as class loss, bbox loss and gIoU loss as shown in the figure 6. The class features are learned well than the other features as the bounding box and IoU.

3.2 Train Detection

Train detection is the process of taking video frames from the camera located at the Railway station from where the train comes along the critical zone as shown in figure 7. The distance between the Railway station and the critical zone should be considered for two reasons. One was switching on the infrasonic sound wave generated fitted at the critical zone and another was to send an alert to the loco pilot along with the train details of the presence of an elephant and reduce the speed of the train. So that if the elephant is not driven away from the critical zone, the pilot can occasionally stop the train to prevent accidents.

Figure 7: Sample of Frame of the Train From Video

	A	B	C
1	Train_ID	Time_poleA	
2	5601	15:12:23	
3	5602	17:14:10	
4	5603	19:50:12	
5	5604	21:25:40	
6	5605	23:16:36	
7	5606	01:30:58	
8	5607	03:10:19	
9	5608	05:10:29	
10	5609	07:05:22	
11	5610	09:07:14	
12	5611	11:12:33	
13	5612	13:12:23	
14	5613	14:03:24	
15	5614	16:03:24	
16	5615	18:31:22	
17	5616	20:30:44	
18	5617	22:58:56	
19	5618	00:16:16	
20	5619	02:03:03	
21	5620	04:18:18	
22	5621	06:25:40	
23	5622	08:16:36	
24	5623	12:00:58	
25	5624	12:10:19	

Figure 8: Snap of Trains Crossing with Time

Based on the experimentation done on BBC World, the train should be detected at least 20 minutes before the spot if the elephant is detected. Also, the details of all the trains crossing the station at a particular time are collected in the database. Those data are converted into .xls format and used for verifying there is any possibility of a train arriving at that time. A snap of the database to check the arrival of train in xls format is shown in figure 8.

4 Results and Discussion

The processing of the video from the camera was done using the OpenCV python library. The video frames are converted into frames at the rate of 24 frames per second. Each frame is considered an image and is tested for the animal by using YOLOv8 medium model. The YOLOv8 medium model works with the CSPDarkNet backbone. It has about 295 layers, 25856883 gradients, and 25856899 parameters. The custom elephant dataset is created using the Open Internet and labeled using roboflow. The txt format required by YOLO for processing the dataset is generated. The framework is trained using pre-trained weight. The experiments were conducted on NVIDIA GEFORCE RTX GPU and 12th Gen Intel(R) Core (TM) i5-12450H, 2.00 GHz, and 12GB RAM. The work was carried out in Pycharm application, Tensor Flow framework and Google API. The sample frames of the video from the camera are shown in figure 9. The videos are taken from the open internet to test the efficiency of the network to get deployed in real-time. Once, the elephants are detected in the system as shown in figure 10, the arrival of the train is checked for the next 20 minutes using the data available already in the database from the railway authorities.

Figure 9: Sample Video Frames in the Critical Zone

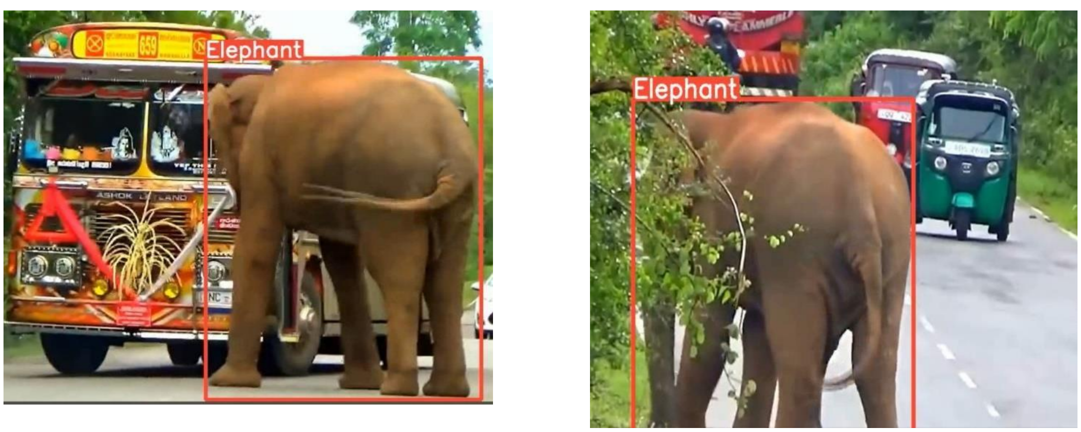

Figure 10: Elephant predicted

Table 1: Comparison of Accuracy of YOLO Models for Detection

Models	Dataset	Accuracy
YOLOv8s	VisDrone2019 (He et al., 2016)	39.3%
UAV-YOLOv8s		47.0%
YOLO + SAM	Custom dataset (Carlos & Escobedo, 2024)	95.1%
YOLOv8-CAB	VOC/COCO Roboflow (n.d.) – *for dataset citation*	97%
YOLOv8 nano	Custom elephant dataset	96%
YOLOv8 medium	Custom elephant dataset	98.4%

The comparison of Accuracy for different YOLO models for detection is illustrated in table 1. It shows that the YOLOv8 medium model has shown better accuracy than that of other models. A sample frame of the video from the railway station and its prediction is shown in figure 11.

Figure 11: Sample Frame from Video – Train Nearing Station and its Prediction

Also, the train is checked for its presence in the camera that is located in the nearby railway station using another CNN with a confidence score above 0.6. This step reduces the false prediction to an extent. The sample video frame of the train nearing the railway station output from the CNN was also shown in the figure 11. The train is predicted with high confidence score.

While the train has arrived at the Railway station or it has crossed the station and moving towards the critical zone camera where the elephant is traced, an infrasonic wave generator has been used to generate the infrasonic frequencies. Comparison of mean average precision for various models and datasets is shown in Table 2 and it represents that the detection CNN has shown better accuracy and speed than other models such as VGG16, ResNet101, Faster R-CNN, and CSP PeleeNet.

Table 2: Comparison of mAP of Various Models and Datasets

Authors	**Dataset**	**Models**	**mAP**
Wang et al., (2020); Prasad et al., (2020)	ImageNet	CSPPeleeNet	70.9%
Ren et al., (2017)	PASCAL VOC 2012	Faster R-CNN	70.4%
	PASCAL VOC 2007	Faster R-CNN	73.2%
He et al., (2016); Li, (2021)	PASCAL VOC 2007 & VOC 2012	ResNet 101	73.2%
		VGG16	76.4%
Detection CNN (proposed)	Custom Train detection Dataset	Detection CNN	91.5%

When the elephants are found in the critical zone and at the same time a train is detected that has passed the station, the system can activate an infrasonic generator to prevent elephants from the area. The simulated infrasonic generator used for this work generates infrasonic waves at the frequency of 1.25 Hertz. The system generates alerts and activates the infrasonic generator when a potential conflict is detected, significantly reducing the risk of elephant-train collisions.

An alert signal in the form of a message is sent to the loco pilot and authorities. The message contains the details of the train as shown in figure 12, so that the loco pilot is aware of the presence of the elephant and can reduce the speed of the train. Also, the Railway authorities are aware of the slowdown of the train and monitor the next train thereby reducing any risks involved. The details in the alert signal are the train ID and the time at which the train arrives at the Station. The time between the message and the train reaching the spot is 20 minutes.

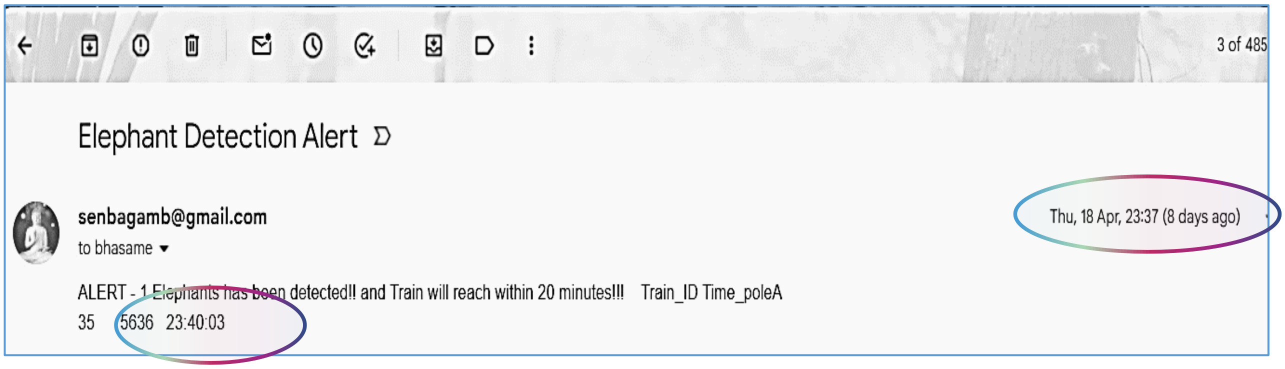

Figure 12: Elephant Alert Message

At the same time, infrasonic generator which is attached to the critical zone camera is turned ON. It produces frequencies from one Hertz to twenty Hertz. These intensive waves help to drive away the elephant from the zone. Thereby stopping the accident and helping the wildlife survival. This scenario helps the joint survival of the elephant and human together. It can also be implemented in the elephant roaming boundaries to drive the elephant away from the Human zone.

5 Conclusion

Thus, the proposed methodology has shown an accuracy of 91.5% for train detection and 98.4% for elephant detection. The method proves to adopt wildlife conservation along with surveillance. Thus, the system can be implemented in the surveillance and monitoring applications for public safety while conserving elephants and reducing the risk of accidents. In the future, if this work is deployed, it could be good for both elephants and humans. With the availability of a large dataset, the CNN can show better accuracy and can be implemented globally. Future efforts will focus on refining deep learning models, integrating multi-modal sensor data with different orientations and locations, and deploying real-time monitoring systems to predict and prevent potential conflicts.

References

[1] Animal_detection_2 Image Dataset, https://app.roboflow.com/college-nbbwh/animal_detection_2/7.

[2] Anni, D. J. S., & Sangaiah, A. K. (2015). An early warning system to prevent human elephant conflict and tracking of elephant using seismic sensors. In *Emerging ICT for Bridging the Future-Proceedings of the 49th Annual Convention of the Computer Society of India (CSI) Volume 1* (pp. 595-602). Springer International Publishing.

[3] Assegid, W., & Ketema, G. (2023). Harnessing AI for Early Cancer Detection through Imaging and Genetics. *Clinical Journal for Medicine, Health and Pharmacy*, *1*(1), 1-15.

[4] Balakrishna, K., Mohammed, F., Ullas, C. R., Hema, C. M., & Sonakshi, S. K. (2021). Application of IOT and machine learning in crop protection against animal intrusion. *Global Transitions Proceedings*, *2*(2), 169-174.

[5] Begum, M., Janeera, D. A., & AG, A. K. (2020, February). Internet of things based wild animal infringement identification, diversion and alert system. In *2020 International Conference on Inventive Computation Technologies (ICICT)* (pp. 801-805). IEEE.

[6] Bhadwal, N., Madaan, V., Agrawal, P., Shukla, A., & Kakran, A. (2019, April). Smart border surveillance system using wireless sensor network and computer vision. In *2019 international conference on Automation, Computational and Technology Management (ICACTM)* (pp. 183-190). IEEE.

[7] Carlos, M., & Escobedo, F. (2024). A case study-based model for sustainable business management through blockchain technology in small and medium-sized enterprises. *Global Perspectives in Management*, *2*(2), 41-50.

[8] Dabare, P., Suduwella, C., Sayakkara, A., Sandaruwan, D., Keppitiyagama, C., De Zoysa, K., ... & Voigt, T. (2015, November). Listening to the giants: Using elephant infra-sound to solve the human-elephant conflict. In *Proceedings of the 6th ACM Workshop on Real World Wireless Sensor Networks* (pp. 23-26).

[9] Garstang, M. (2010). Elephant infrasounds: long-range communication. In *Handbook of Behavioral Neuroscience* (Vol. 19, pp. 57-67). Elsevier.

[10] Giordano, S., Seitanidis, I., Ojo, M., Adami, D., & Vignoli, F. (2018, March). IoT solutions for crop protection against wild animal attacks. In *2018 IEEE international conference on Environmental Engineering (EE)* (pp. 1-5). IEEE.

[11] Gorhum, J., Muir, T., Slack, C. M., Barlett, M. L., Hawkins, T., Tinney, C., & Baars, W. (2013, June). Pneumatic infrasound source: Theory and experiment. In *Proceedings of Meetings on Acoustics* (Vol. 19, No. 1). AIP Publishing.

[12] Gupta, A., & Joshi, T. (2025). Frame work of sustainable wastewater treatment methods and technologies. *International Journal of SDG's Prospects and Breakthroughs*, *3*(1), 1-7.

[13] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

[14] Hou, J., He, Y., Yang, H., Connor, T., Gao, J., Wang, Y., ... & Zhou, S. (2020). Identification of animal individuals using deep learning: A case study of giant panda. *Biological Conservation*, *242*, 108414. https://doi.org/10.1016/j.biocon.2020.108414

[15] Ibraheam, M., Gebali, F., Li, K. F., & Sielecki, L. (2020). Animal species recognition using deep learning. In *Advanced Information Networking and Applications: Proceedings of the 34th International Conference on Advanced Information Networking and Applications (AINA-2020)* (pp. 523-532). Springer International Publishing.

[16] Ji, P., & Zhu, Q. (2022, June). Research on embedded animal recognition system based on yolo. In *2022 6th international conference on robotics and automation sciences (ICRAS)* (pp. 265-269). IEEE. https://doi.org/10.1109/ICRAS55217.2022.9842099.

[17] Jin, X., Sarkar, S., Ray, A., Gupta, S., & Damarla, T. (2011). Target detection and classification using seismic and PIR sensors. *IEEE Sensors Journal*, *12*(6), 1709-1718.

[18] Kurian, N., & Sultana, Z. (2024). Traditional Ecological Knowledge and Demographic Resilience in Marginalized Societies. *Progression journal of Human Demography and Anthropology*, 17-21.

[19] Li, W. (2021, March). Analysis of object detection performance based on Faster R-CNN. In *Journal of Physics: Conference Series* (Vol. 1827, No. 1, p. 012085). IOP Publishing.

[20] Malhotra, R., & Iyer, A. (2024). Developing an Effective Training System for Interventional Pulmonology Education through Digital Learning. *Global Journal of Medical Terminology Research and Informatics*, *2*(4), 1-8.

[21] Mathur, P., Nielsen, R. H., Prasad, N. R., & Prasad, R. (2014, May). Wildlife conservation and rail track monitoring using wireless sensor networks. In *2014 4th International conference on wireless communications, vehicular technology, information theory and aerospace & electronic systems (VITAE)* (pp. 1-4). IEEE.

[22] Mekonen, S. (2020). Coexistence between human and wildlife: the nature, causes and mitigations of human wildlife conflict around Bale Mountains National Park, Southeast Ethiopia. *BMC Ecology, 20*(51), 1-9.

[23] Mystery of Elephant Infra sounds Revealed, Animal Super Senses, BBC Earth https://www.youtube.com/watch?v=uQfDazQ9Rkg.

[24] Ngama, S., Korte, L., Bindelle, J., Vermeulen, C., & Poulsen, J. R. (2016). How bees deter elephants: Beehive trials with forest elephants (Loxodonta africana cyclotis) in Gabon. *PLoS One*, *11*(5), e0155690. https://doi.org/10.1371/journal.pone.0155690

[25] Norouzzadeh, M. S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M. S., Packer, C., & Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. *Proceedings of the National Academy of Sciences*, *115*(25), E5716-E5725.

[26] Panda, P. K., Kumar, C. S., Vivek, B. S., Balachandra, M., & Dargar, S. K. (2022, February). Implementation of a wild animal intrusion detection model based on internet of things. In *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)* (pp. 1256-1261). IEEE.

[27] Patil, A. R., & Mali, A. S. (2023). Implementation of IoT based wild animal intrusion detection system. *International Journal of Emerging Technologies and Innovative Research (JETIR)*, *10*(10), 419–424.

[28] Prasad, S. S., Kirankrishna, S., & Simonthomas, S. (2020). Automated Gross Cutting and Disease Detection in Farming Sector Using Robotics and Iot. *International Journal of Advances in Engineering and Emerging Technology*, *11*(1), 57-66.

[29] Rakesh, N., Mohan, B. A., Kumaran, U., Prakash, G. L., Arul, R., & Thirugnanasambandam, K. (2024). Machine Learning-Driven Strategies for Customer Retention and Financial Improvement. *Archives for Technical Sciences*, *2*(31), 269-283. https://doi.org/10.70102/afts.2024.1631.269.

[30] Ren, S., He, K., Girshick, R., & Sun, J. (2017). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, *39*(06), 1137-1149.

[31] Shaffer, L. J., Khadka, K. K., Van Den Hoek, J., & Naithani, K. J. (2019). Human-elephant conflict: A review of current management strategies and future directions. *Frontiers in Ecology and Evolution*, *6*, 235.

[32] Sharma, P., Chettri, N., & Wangchuk, K. (2021). Human–wildlife conflict in the roof of the world: Understanding multidimensional perspectives through a systematic review. *Ecology and evolution*, *11*(17), 11569-11586.

[33] Sindhu, S. (2023). The Effects of Interval Uncertainties and Dynamic Analysis of Rotating Systems with Uncertainty. *Association Journal of Interdisciplinary Technics in Engineering Mechanics*, *1*(1), 49-54.

[34] Soy, A., & Balkrishna, S. M. (2024). Automated detection of aquatic animals using deep learning techniques. *Int. J. Aquat. Res. Environ. Stud.*, *4*(Suppl. 1), 1-6.

[35] Train detector Image Dataset: https://app.roboflow.com/college-nbbwh/train-detector-hp2/6.

[36] Villa, A. G., Salazar, A., & Vargas, F. (2017). Towards automatic wild animal monitoring: Identification of animal species in camera-trap images using very deep convolutional neural networks. *Ecological informatics*, *41*, 24-32.

[37] Wang, C. Y., Liao, H. Y. M., Wu, Y. H., Chen, P. Y., Hsieh, J. W., & Yeh, I. H. (2020). CSPNet: A new backbone that can enhance learning capability of CNN. *In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops* (pp. 390-391).

[38] Yadav, R. K., Mishra, A. K., Saini, J. B., Pant, H., Biradar, R. G., & Waghodekar, P. (2024). A Model for Brain Tumor Detection Using a Modified Convolution Layer ResNet-50. *Indian Journal of Information Sources and Services*, *14*(1), 29-38.

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