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AI-Powered Monitoring for Mitigating Human-Animal Conflicts in Agricultural and Forest Zones

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Abstract:- Human-animal conflicts pose a significant challenge in forest zones and agricultural fields, leading to resource losses and threats to endangered wildlife. These conflicts have escalated in recent years, necessitating innovative solutions for continuous monitoring and intervention. This study presents a novel approach for mitigating such conflicts by leveraging image processing and Artificial Intelligence (AI). Motion detection techniques are employed to identify activity, and content-based image classification algorithms analyze the captured visuals. The proposed method integrates advanced feature extractors, data augmentation, and AI to develop a robust detection network. Additionally, the system enhances safety analysis and certification for high-speed trains by identifying objects and animals in real time. Using the COCO dataset for training and validation, the study demonstrates the potential of AI to streamline conventional safety measures and ensure the coexistence of humans and animals in ecologically sensitive areas.

Keywords: Railway track, artificial intelligence, detect animals, Convolutional neural network, safety analysis.

I. INTRODUCTION

Deep learning-based animal detection is a fast-expanding topic that uses machine learning algorithms to recognise and categorise animals in pictures or movies. A sort of artificial intelligence called deep learning uses massive amounts of data to train neural networks to find patterns and make detections. Animal behaviour analysis, livestock management, and wildlife conservation are just a few of the numerous uses for animal detection research. Researchers can obtain important insights into animal populations and behaviour by using deep learning algorithms to automatically identify and classify animals in photos or videos. These insights can help guide conservation efforts, enhance our knowledge of animal detection, and improve livestock management techniques.

Global railway transport has expanded significantly in the last few decades. In China, many people prefer using railway transportation due to its high speed, punctuality, and affordable fares, which are made possible via control optimisation. Stricter regulations for railway safety are the outcome of the rapid growth in passenger traffic. Railway transport depends heavily on safety, which also affects social politics, the economy, the enterprise's bottom line, and production efficiency. When operating at high speeds, the electric multiple units (EMU) are prone to attracting unwanted objects, like plastic bags attached to the rails and entangled in the bottom bogie, as well as cable and equipment gaps. These can result in smoke and odours, as well as equipment short circuits and fires.

For this reason, it's critical to promptly identify any foreign objects connected to the EMU's bottom in order to ensure train safety. There are now two detection options available for this foreign matter examination. The manual inspection method has numerous shortcomings, including excessive time consumption, decreased productivity, and—above all—the inability to ensure the safety of the engineers. TEDS combines network control technologies, precise positioning, real-time image processing, image recognition, and picture acquisition. It has the ability to identify safety risks and unexpected malfunctions online, as well as perform dynamic visual detection at the EMU's exterior. Fig 1 shows the picture of animal crossing the track.

Fig 1: image of animal crossing railway tracks

II. BACKGROUND

[1] Deep learning techniques have been increasingly successful recently in the object detection domains due to their robust feature extraction capabilities. The learning process of the human visual system, which is built on numerous layers consisting of linear and nonlinear units to acquire the ability to learn complicated data, is the model for the deep neural convolutional network. Deep learning techniques don't require as much feature extraction effort on foreign matter as classic techniques do. [2] Furthermore, when used in many sectors,

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deep learning techniques perform significantly better than conventional techniques—sometimes even surpassing human-level techniques. Deep learning techniques enable amazing performance in the inspection and detection of a wide range of objects with varying sizes, colours, and forms under various settings. As a result, deep learning-based target detection has progressively supplanted more conventional techniques.

[3] Deep learning technology is now widely used in railroads as machine learning has progressed. Metro facilities are utilising Google's InceptionV3 deep neural network model. The method employed to identify railway track fasteners was based on deep learning. Arcs in pantograph-catenary systems were identified using a deep learning method [4]. To build an all-inclusive tunnel fracture detection and analysis system, an efficient and impartial system for identifying tunnel cracks based on the ResNet18 CNN.

To determine railway geometries and possibly hazardous obstructions, A deep learning approach-based FB-NET identification model [5]. Thus far, a number of deep learning systems have demonstrated good performance in identifying targets; however, no one has employed deep learning techniques to identify foreign bodies hidden beneath high-speed train bodies. [6] In order to detect foreign matter, the most recent DL -based target recognition techniques, SSD and Faster R-CNN, are developed. [7] This study shows how well these techniques work. With regard to these detection models, many feature extractors were used in the original SSD and Faster R-CNN models, which were only provided with a single feature extractor. The use of data augmentation and transfer learning techniques improved the efficacy of foreign matter underbody detection [8].

[9] suggests two instantaneous methods for electric cars parked in charging stations to engage in secondary frequency regulation. Based on area control error and regulation requirements, these solutions may guarantee EV charging demands while reducing frequency deviation and generator regulation by 12.66% and 16.78%, respectively. [10] How well Google's Inception V3 DCNN classifies photos of common facilities in metro tunnels. Comparing the model with other similar DCNNs, it uses less computing power and has less parameters and complexity. When compared to the current approach, the model's mean average precision (mAP) of 90.81% showed a notable improvement in metro barrier detection.

[11] Innovative methods for railway track fastener defect detection using image processing technologies and DL networks. The method improves track safety and reduces maintenance costs. It uses Dense-SIFT features for better performance, VGG16 for defect detection, and Faster R-CNN for faster detection. The method allows simultaneous fastener positioning and recognition, reducing detection time by one-tenth of other methods. [12] The detection network and the region proposal network (RPN) exchange full-image convolutional features, which allows for almost cost-free region proposals. High-quality region suggestions are generated by RPNs through end-to-end training, which predicts object limits and objectness scores. On PASCAL VOC 2007 and 2012, the detection system uses 300 suggestions per image to achieve state-of-the-art item detection accuracy.

[13] Animal accidents on railway tracks pose a threat to wildlife populations, particularly elephants, rhinos, and buffalo. Machine learning technologies, including deep learning, have been proposed to address this issue. A model based on CNN has been developed to classify images as animal detection on tracks. The model, trained with normalization and pooling layers, achieved an accuracy of 96% compared to other models. [14] Railways are popular due to increased bus ticket costs, requiring continuous monitoring and inspection of tracks. Hand-held inspections are inefficient and time-consuming. Animal conservation is crucial, but trains can interfere with local fauna, leading to animal deaths.

The movement of people and products increases the direct mortality from car collisions and decreases the availability of habitat, which contributes to the sixth mass extinction of species. A system for managing AVC is built by mapping the collision risk between trains and ungulates using sensors integrated in transport infrastructure (TI). [15]. [16] To save larger animals from railway track collisions using Machine Learning models. It uses an ESP32 camera, YOLOv3 Convolutional Neural Network, and ultrasonic sensor to detect obstacles and prevent collisions, with improved accuracy and confidence scores. [17] The railway industry is undergoing digitization, posing challenges in integrating new technologies into safety-critical systems. This study presents 21 potential use cases and analyses threats using Attack Graphs. It identifies 21 countermeasures needing further research or standardization to ensure system security.

III. PROPOSED METHODS

An innovative Deep Learning Algorithm Convolutional Neural Network for identifying animal crossings on railway lines is shown by the suggested system demonstrated in fig 2. With the technology, high-definition image cameras take the place of current contact methods, enabling feature extraction for preprocessing. Compared to existing approaches, it is more efficient and overcomes faults. Oil spill locations are detected by multiple hidden layers, which then compute and display the area in Python shell. The flowchart of the proposed methods was derived in fig 3.

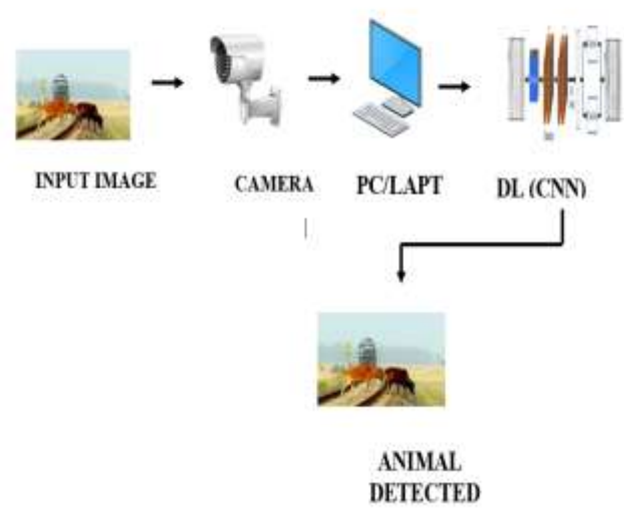

Fig 2: block diagram of the proposed diagram

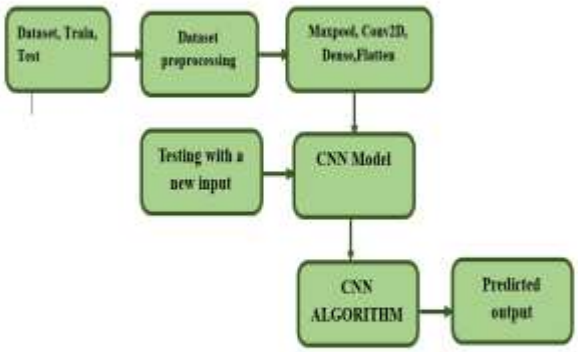

Fig 3: architecture of the proposed method

As seen in Fig 4, target recognition and feature extraction are the two primary steps in CNN-based target detection.

In order to determine the target's classification and position, the image is fed into the detection network and examined by a deep network. Target detection techniques based on deep learning come in two varieties. One type of neural network, known as one-stage target detection, eliminates the need for an area proposal technique by turning object detection directly into a regression problem. The one-stage object method's basic concept is to use the recognizer to quickly identify an image after taking pictures at several evenly spaced spots. The detection process is completed in a single step. Thus, the primary goal of one-stage target identification techniques is inspection speed. The two-stage target identification method combines CNN classification with region recommendation to build a model.

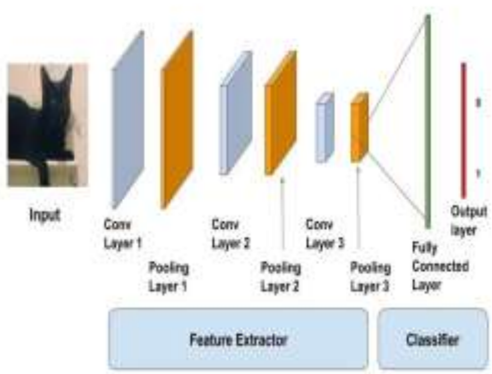

Fig 4: CNN layers

A. Detecting animals

In order to analyse photos from cameras placed on the train or along the tracks, a deep convolutional neural network (CNN) is used. Using a sizable dataset of photos of animals in a range of positions and lighting scenarios, CNNs can be taught to identify patterns and characteristics unique to identifying different species.

B. Interfacing The Camera

Computer vision is one of the most crucial phases in picture processing. Consequently, we need to link our deep learning model to the camera. since all items in the real world will be visible to the computer via the camera. Use a cable to connect a digital camera to a computer or other display device. When an animal is recognised, the camera takes pictures of it and sends them to the display device so that it may be used to view the dimension model, etc. Computer vision, for instance, can be used to help cars. It can recognise and respond to various items on the road, such as pedestrians, traffic lights, signs, and so on.

The computer can carry out jobs with the same efficiency as humans thanks to computer vision. The two primary tasks are listed below and are as follows:

- Object Classification: In this process, new objects are classified as falling into one or more of your training categories using a model that has been trained on a dataset of specific objects.
- Object Identification**:** In this step, our model will recognise a specific instance of an object.

C.Python

Pythonis a high-level, interpreted programming language that abstracts away complicated aspects from its code so that even non-programmers may understand it. It provides faster development times than fully compiling languages like C and C++, but significantly slower execution times. It is easy to code and is a developer-friendly language. Integration with other languages, such as C and C++, is simple.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The model's detection speed is a crucial metric for evaluating its efficacy in real time. Table 1 shows the data of the detection model that take a lot of time. Given its superior precision over other feature extractors and consequently large parameter set (up to 130 million), the VGG network consumes the most time on average in both the more rapid R-CNN and SSD recognition models. The feature extractor that uses the same recognition model but has less parameters is quicker. As a result, the number of extraction of features parameters in the network directly affects the detection rate of the network. Because it can balance both performance and precision, the SSD model that uses Inception V2 as the feature extraction network is superior when it comes to identifying foreign bodies under high-speed trains. To illustrate the effectiveness of the proposed method in foreign matter detection, researchers compared the Inception V2 combo of more rapid R-CNN and SSD with the top-performing strategy in the conventional target identification method, called discriminatively trained part-based models (DPM). The DPM approach uses feature templates to do sliding frame mirroring detection while detecting images. It derives its features from HOG features, that are not produced by deep training.

TABLE 1: Experimental results with data augmentation.

Detect Model	Precision	Average Time
VGG	90.20%	164 ms

ResNEt	88.50%	137 ms
Inception V2	89.70%	83 ms
Mobile Net	81.30%	41 ms

A. Detection of animals

It is difficult to give a thorough analysis of the findings of the animal detection study because they depend on the kind of technology used, the surrounding circumstances, and the particular species of animals. High precision is essential for identifying animals (fig 5) and averting unfavourable consequences. Python is an evolving, high-level, interpretable, object-centered, and procedural code language. It is simple to develop and can be seamlessly integrated with other languages. The output module was presented in fig 6.

Fig 5: Animal detection

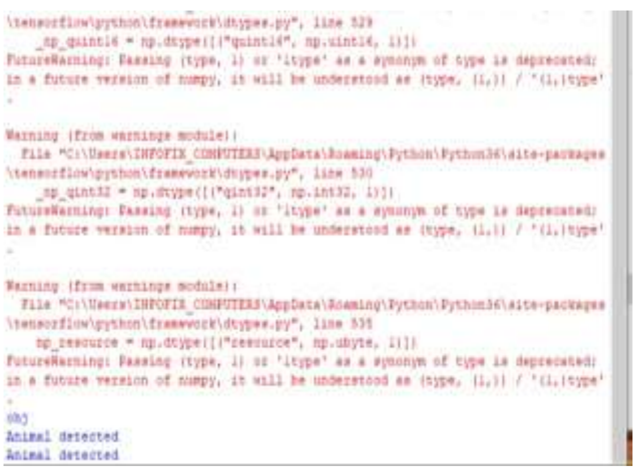

Fig 6: Output of the animal detection module

V. CONCLUSION

The ability to identify foreign objects in train bottoms is critical to railway safety. When compared to conventional methods, deep learning techniques have been demonstrated to increase detection speed and precision. CNNs are efficient artificial neural networks that are utilised for item, animal, and picture categorization. By identifying new photographs as including animals based on attributes they learn from big datasets, they enable real-time applications for animal detection. The experiment achieved 89.7% detection speed, while the SSD+MobileNet combination earned the fastest detection speed with 81.3% precision. Up to 8.9% more accuracy was achieved overall thanks to data augmentation techniques.

ABBREVIATION

AI - Artificial Intelligence

DL- Deep Learning

EMU - Electric Multiple Units

CNN- Convolutional Neural Network

MAP - Mean Average Precision

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