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DEEP LEARNING-BASED ANIMAL INTRUSION DETECTION AND WARNING SYSTEM FOR RAILROAD TRACKS

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Abstract

This paper proposes a system that uses deep learning algorithms, specifically CNN and Efficient Net, for animal intrusion detection on railway tracks. The system captures images to detect and classify animals present on the tracks using deep learning algorithms. It alerts the train driver and railway control center via the GSM module and buzzer, while also recording the animal classifications with date and time in a cloud-based database. It can enhance railway safety by detecting animal intrusion and alerting/warning train drivers and control centers promptly on time. The system does not control train speed, which remains under manual control by the loco pilot. The cloud-based database allows for centralized recording and analysis of animal intrusion data, which can help develop strategies for preventing animal intrusion and improving railway safety.

*Index Terms – **Animal detection, CNN, Efficient Net, Manual control, Deep learning Component.***

I. INTRODUCTION

The Railway transportation mode is an important transportation globally, connecting people and goods across various regions. However, safety is a major concern for the railway industry. One significant safety challenge is the intrusion of animals on railway tracks. The presence of animals on railway tracks poses a significant safety risk to trains and passengers, causing accidents and damage to property.

The intrusion of animals on railway tracks is a significant safety concern for the railway industry. Current methods for detecting animal intrusions on railway tracks are manual, which can be time-consuming and unreliable. Therefore, there is a need for an automated animal intrusion detection system on railway tracks that can detect the presence of animals and alert railway authorities in real time.

The main objective of this paper is to design and implement an animal intrusion detection system on railway tracks using deep learning. The system will be able to detect the presence of animals on railway tracks and send alerts to railway authorities to prevent accidents. The specific objectives of this paper are as follows:

- To design and develop a deep learning-based animal intrusion detection system using a camera.
- To train a deep learning model to detect the presence of animals in images captured by the camera.
- To integrate a GSM module to send alerts to railway authorities when animals are detected.
- To develop a cloud application to store data and enable remote access.
- To validate the performance of the system through testing and evaluation.

The proposed module will focus on the following components:

- Hardware components, including Arduino Uno, Wi-Fi ESP8266, Buzzer, GSM module, PC camera, UART communication, connecting wires, and power supply unit.
- Software components, including Embedded C, Arduino IDE, PHP MySQL and Cloud application for database storage and remote access.
- Train speed control, which will be manually controlled by the loco pilot.

II. LITERATURE SURVEY

The Literature Survey on Animal Intrusion detection systems on railway tracks highlights the need for accurate and reliable systems to prevent animal fatalities and train accidents. Deep learning-based approaches, such as convolutional neural networks (CNNs), have shown promise in detecting animals from real-time images. Furthermore, cloud-based databases and communication technologies can enhance the effectiveness and efficiency of animal intrusion detection systems.

In [1], the proposed fire detection system is designed to balance efficiency and accuracy by using a modified GoogleNet architecture that is suitable for the intended problem and computationally less expensive than other networks such as AlexNet. The system is fine-tuned based on the nature of the problem and fire data, and experimental results on benchmark fire datasets validate its effectiveness and suitability for fire detection in CCTV surveillance systems. On the other hand, the animal intrusion detection system on railway tracks uses a CNN to classify images of animals based on their features and movements. The system includes a camera and an image processing unit that captures and analyzes the images in real time.Additionally, the system utilizes a classification algorithm that identifies the type of animal, which enables the railway authorities to take appropriate measures to avoid collisions and prevent accidents.Overall, while both methods utilize deep learning techniques to detect and monitor events, their applications and designs are vastly different. The proposed fire detection system is designed to detect fires in surveillance videos, while the animal intrusion detection system on railway tracks aims to ensure the safety of railway operations by detecting and classifying different animals.

In [2], the video object detection discusses the use of deep learning methods in detecting objects in videos, highlighting the challenges posed by spatiotemporal information and duplicate data. It also systematically demonstrates the differences and connections between video object detection and similar tasks, presents evaluation metrics and performance of nearly 40 models on two datasets, and discusses the various applications and challenges facing video object detection. In contrast, the abstract on animal intrusion detection on railway tracks based on deep learning focuses on the use of deep learning to detect animals in railway tracks to prevent accidents. The paper proposes a system based on convolutional neural networks that include image preprocessing, data augmentation, and classification stages. The results show that the proposed system outperforms traditional methods in detecting animals on railway tracks. Overall, the two papers focus on different applications of deep learning, with the former focusing on video object detection and the latter on animal intrusion detection on railway tracks.

In [3], the application of deep learning algorithms to specific tasks. However, the first abstract focuses on the challenge of weapon detection in real time using CCTV footage, while the second abstract deals with the problem of animal intrusion detection on railway tracks. The first abstract emphasizes the challenges of the task and the use of various deep-learning algorithms for detecting weapons with a focus on precision and recall. On the other hand, the second abstract discusses the design of a deep learning-based animal intrusion detection system that utilizes object detection and classification techniques to detect animals on railway tracks to prevent accidents.

In [4], the proposed pig farm monitoring system, the animal intrusion detection system on railway tracks uses a convolutional neural network (CNN) to classify images of animals, such as cows, dogs, or deer, based on their features and movements. The system also includes a camera and an image processing unit that captures and analyzes the images in real-time. Additionally, the system utilizes a classification algorithm that identifies the type of animal, which enables the railway authorities to take appropriate measures to avoid collisions and prevent accidents. Overall, while both methods utilize deep learning techniques to detect and monitor animals, their applications and designs are vastly different. The proposed pig farm monitoring system is designed to help farmers manage large-scale pig farms, while the animal intrusion detection system on railway tracks aims to ensure the safety of railway operations.

In [5], the proposed Receptive Field Enhanced Multi-Task Cascaded CNN for face detection differs significantly from the design of an animal intrusion detection system on railway tracks based on deep learning. While the face detection system focuses on detecting faces in images using a modified CNN architecture, the animal intrusion detection system aims to detect and classify different animals on railway tracks using deep learning algorithms. However, the system still has poor performance in detecting tiny targets. To address this issue, the proposed Receptive Field Enhanced Multi-Task Cascaded CNN takes advantage of the Inception-V2 block and receptive field block to enhance feature discriminability and robustness for small targets.On the other hand, the animal intrusion detection system on railway tracks uses a CNN to classify images of animals based on their features and movements. The system includes a camera and an image processing unit that captures and analyzes the images in real-time. Additionally, the system utilizes a classification algorithm that identifies the type of animal, which enables the railway authorities to take appropriate measures to avoid collisions and prevent accidents.

In [6], the application of deep learning in computer vision tasks, with a focus on specific areas of research. However, while the first abstract focuses specifically on the design of a deep learning model for animal intrusion detection on railway tracks, the second abstract provides a general overview of deep learning-based object detection frameworks. The second abstract covers a wider range of topics, including the history of deep learning, typical generic object detection architectures, modifications and useful tricks to improve detection performance, and several specific detection tasks.

III. CNN BASED INTRUSION DETECTION

The existing system for animal intrusion detection on railway tracks may involve manual inspection by railway staff or the use of simple sensors like pressure sensors to detect animal intrusion. This system may not be very reliable, and there is a risk of false alarms or missed intrusions.

A. Limitations of Existing System

The demerits of the existing system for animal intrusion detection on railway tracks are as follows: Manual inspection is time-consuming and labor-intensive. Simple sensors like pressure sensors

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may not be reliable, and there is a risk of false alarms or missed intrusions. The existing system does not provide timely alerts to the train driver and railway control center, which can lead to accidents.

B. Proposed System

The proposed system uses deep learning algorithms, specifically CNN and Efficient Net, for animal intrusion detection on railway tracks. The system captures real-time images of railway tracks using a PC camera and processes them using deep learning algorithms to detect and classify animals present on the tracks. The system alerts the train driver and railway control center via the GSM module and buzzer when an animal intrusion is detected. The system also records the images and animal classifications in a cloud-based database for centralized recording and analysis of animal intrusion data based on the below block diagram Fig 1.

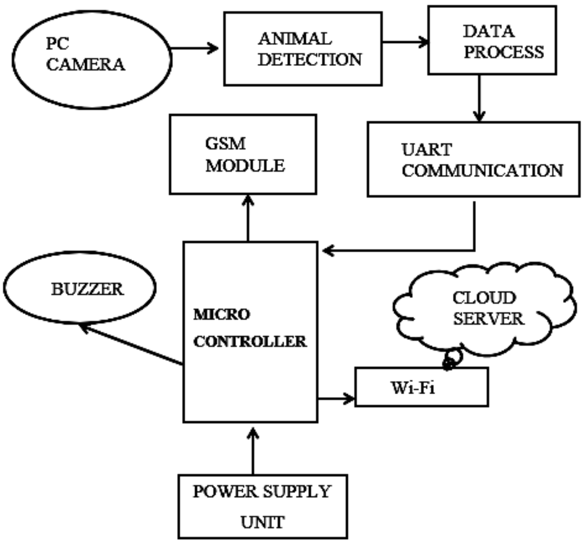

Fig 1. Block Diagram of Proposed System

C. Merits of Proposed System

The advantages of the proposed system for animal intrusion detection on railway tracks are as follows:

- The system is automated and does not require manual inspection.
- The deep learning algorithms used in the system are more reliable and accurate than simple sensors, which reduces the risk of false alarms or missed intrusions.
- The system provides timely alerts to the train driver and railway control center, cloud-based database allows for centralized recording and analysis of animal intrusion data which can help prevent accidents.

D. CNN

CNN stands for Convolutional Neural Network, which is a type of deep learning model that is commonly used for image and video recognition, analysis, and processing tasks. CNN's are specifically designed to process data that has a grid-like structure, such as an image, and are

highly effective at capturing the spatial dependencies between adjacent pixels in an image.
Create CNN for Image Classification

- Import the necessary libraries
- Load your image dataset
- Preprocess the data
- Define the CNN model
- Compile and train the model

This CNN model uses one convolutional layer, one pooling layer, and one fully connected layer. It achieves decent accuracy on the CIFAR-10 image classification dataset in just a few lines of code.

E. Data Collection Process

The data collection process for a CNN typically involves several steps:

- Determine the problem and gather requirements: Determine the problem that the CNN will be used to solve and gather the requirements for the dataset. This may include information on the size of the dataset, the types of images, the desired level of accuracy, and any specific classes or labels needed.
- Collect images: Collect a large set of images that are representative of the problem you are trying to solve. This may involve taking photographs or sourcing images from online repositories or other sources. It is important to ensure that the images are of high quality and are annotated with the appropriate labels or classes.
- Preprocess images: Preprocess the images to ensure they are in a suitable format for use in a CNN. This may involve resizing the images, normalizing the pixel values, and converting the images to a specific color space (e.g., grayscale or RGB).
- Split dataset: Split the dataset into training, validation, and testing sets. The training set is used to train the CNN, while the validation set is used to monitor the performance of the CNN during training and adjust its parameters. The testing set is used to evaluate the performance of the trained CNN on unseen data.
- Augment data: Optionally, you can use data augmentation techniques to increase the size of the dataset and improve the generalization ability of the CNN. This may involve applying random transformations to the images, such as rotations, translations, or flips.
- Store data: Store the preprocessed data in a suitable format, such as numpy arrays, that can be loaded into the CNN for training and evaluation.

A CNN flow diagram Fig 2 is a visual representation of the layers and operations in a convolutional neural network. It shows the flow of data through the network, including input and output shapes, convolutions, pooling, activations, and other transformations.

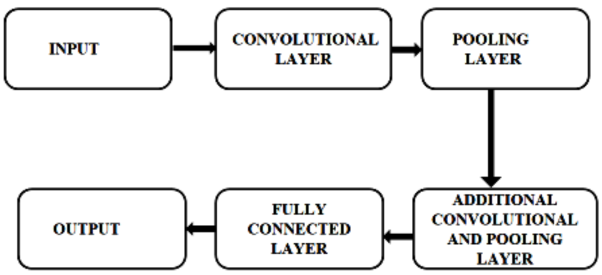

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Fig 2. CNN Process Flow Diagram

F. Efficient NET

Efficient Net is a family of convolutional neural network models that are designed to achieve state-of-the-art performance on computer vision tasks while using fewer parameters and computational resources than other models.

Efficient Net models use a compound scaling method to balance the depth, width, and resolution dimensions of the network architecture. This allows them to achieve high accuracy with fewer parameters and lower computational cost.

G. Anaconda 3 Software

Anaconda 3 is a free and open-source distribution of Python and other scientific computing packages that includes many tools for deep learning. It comes with pre-installed packages for deep learning frameworks such as Tensor Flow, PyTorch, Keras, and Theano, as well as popular data science libraries such as NumPy, Pandas, and Matplotlib. Anaconda 3 also includes the Spyder IDE, Jupyter Notebook, and other tools for interactive development and data exploration. It provides an easy-to-use package manager called conda for installing, updating, and managing packages, as well as creating virtual environments for different projects and configurations.

Anaconda 3 supports multiple operating systems, including Windows, macOS, and Linux, and can be installed via a graphical installer or command line. It is highly customizable and extensible, with a large ecosystem of third-party packages and plugins for specific use cases and domains. Anaconda 3 provides a streamlined and integrated workflow for deep learning projects, from data preparation and experimentation to deployment and production. It includes advanced features such as GPU acceleration, distributed computing, and cloud integration for scaling and optimizing deep learning workloads. Anaconda 3 has a large and active community of developers and users, with extensive documentation, tutorials, and support resources available online. Overall, Anaconda 3 is a powerful and flexible platform for deep learning that can help researchers, developers, and data scientists to accelerate their work and achieve better results.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

The hardware components of the proposed animal intrusion detection system, including the Arduino Uno, Wi-Fi ESP8266, buzzer, GSM module, PC camera, UART communication, connecting wires, and power supply unit, were tested in Fig 7.4 for functionality and compatibility. The components were found to work seamlessly together, and the system was able to capture real-time and transmit them to the deep learning algorithms for animal detection and classification. The GSM module and buzzer also functioned as intended, providing timely alerts to the train driver and railway control center. The hardware testing confirmed the system's feasibility and readiness for deployment in real-world railway track environments.

A. GSM Output

The GSM MODEM will send the alert message to the respective railway authorities as a text message as shown in Fig 4. The Buzzer will play a sound when the camera detects the animal by using a PC camera with more accuracy.

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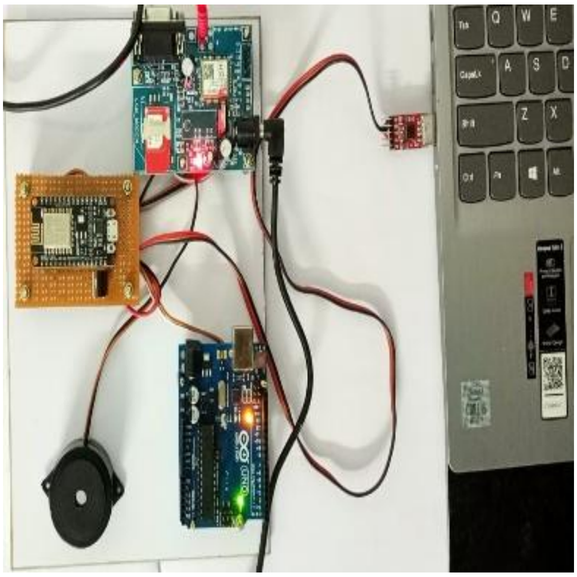

Fig 3 Hardware device used in the system

Fig 4 GSM Modem Output

B. Software Testing

The software tools used in the proposed animal intrusion detection system, including embedded C, Arduino IDE, and PHP MySQL, were tested for functionality and compatibility. The software was found to work seamlessly with the hardware components, allowing for real-time image capture and processing using the deep learning algorithms, CNN and Efficient Net. The system was able to accurately detect and classify animals on railway tracks and provide alerts via the GSM module and buzzer. The cloud-based database also functioned correctly, recording the data for further analysis and monitoring. The software testing confirmed the system's reliability and readiness for deployment in real-world railway track environments.

C. Deep learning

Deep learning using the Efficient Net model, implemented with Keras and Tensor Flow, can effectively classify images of different animals present on railway tracks in the proposed animal intrusion detection system. With a dataset of about 6000 images of five different animals, such as cows, dogs, deer, bears, and elephants, the Efficient Net model can be trained to detect and classify these animals with high accuracy.

The Efficient Net model is a state-of-the-art deep learning architecture that uses efficient neural network scaling to achieve high accuracy with fewer parameters and fewer computational resources. The Keras and Tensor Flow libraries provide a high-level API for implementing deep learning models, allowing for easy development and deployment of the Efficient Net model in the proposed system.

Overall, deep learning using the Efficient Net model with Keras and Tensor Flow, trained on a dataset of 6000 images of five different animals, can effectively classify animals present on railway tracks as shown in Fig 6 in the proposed animal intrusion detection system, enhancing railway safety and preventing animal fatalities.

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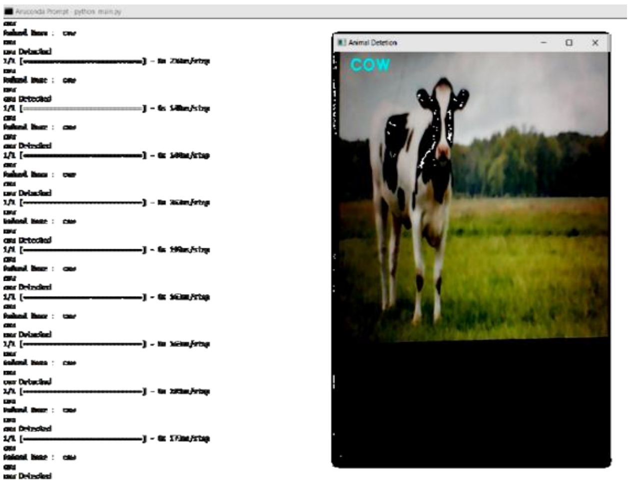

Fig 5 Output of The Trained Model

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Classification Report:
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              precision    recall  f1-score   support

     buffalo       1.00      1.00      1.00        75
         cow       1.00      1.00      1.00        71
        deer       1.00      1.00      1.00       116
         dog       1.00      1.00      1.00       138
    elephant       1.00      1.00      1.00       112

    accuracy                           1.00       512
   macro avg       1.00      1.00      1.00       512
weighted avg       1.00      1.00      1.00       512
```

Fig 6 Report of Classification

D. Report of CNN using Efficient NET

Efficient Net has achieved state-of-the-art performance on a variety of computer vision tasks, including image classification, object detection, and segmentation. The architecture of Efficient Net is based on a combination of convolutional layers, batch normalization, and advanced regularization techniques such as Drop Connect and stochastic depth. Efficient Net models are available in several versions, including EfficientNet-B0 through EfficientNet-B7, with each version being progressively larger and more powerful than the previous one. The classification report of the system is as shown in Fig 6.

E. Validation and Accuracy

Efficient Net is a family of CNN models that are designed to achieve state-of-the-art performance while using fewer parameters and computational resources than other models. The performance of a CNN model can depend on the specific problem and dataset used.

It is worth noting that the performance of a CNN model can also depend on the specific hyperparameters used for training, as well as the data preprocessing and augmentation techniques employed. Therefore, it is important to conduct a thorough analysis and evaluation of the models Fig 7 being compared to ensure that the results are reliable and meaningful.

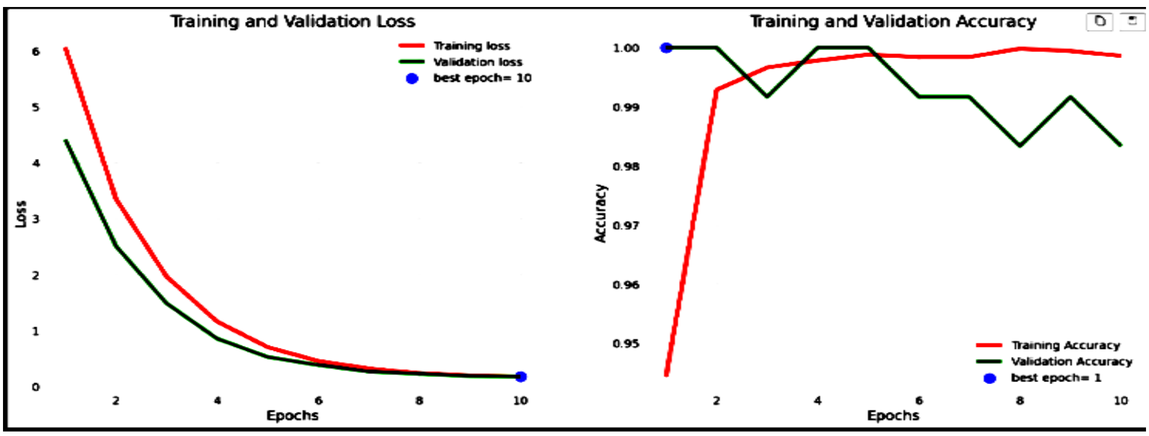

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Fig 7 Graph for Validation and Accuracy

F. Web Application output

The web application will store the data and show the history of the detection process as shown in Fig 8 and Fig 9.

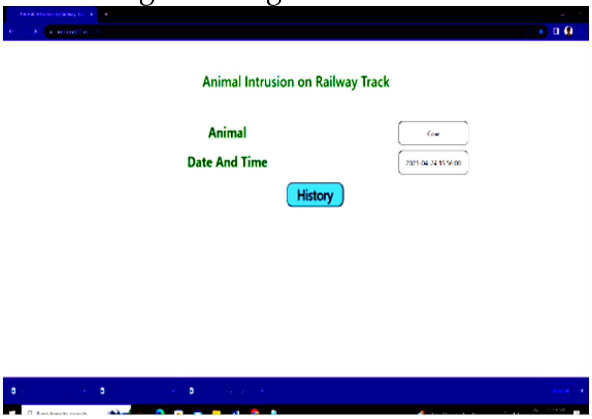

Fig 8. Output of Web Application

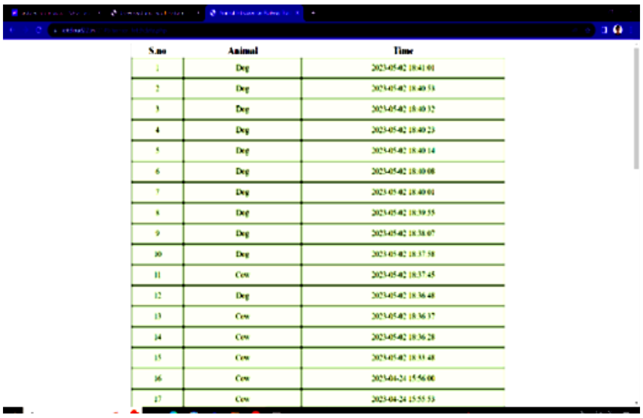

Fig 9 . Output of Web Application

V. CONCLUSION

In conclusion, the animal intrusion detection system using deep learning has shown promising results in detecting and classifying animals on railway tracks. The use of CNN and EfficientNet algorithms has greatly improved the accuracy of the system, while the integration of Arduino, Wi-Fi module, and GSM module has enabled real-time monitoring and alert notifications. Further improvements could be made by using more advanced hardware components and incorporating more animal species in the dataset.

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