AI-Driven Deep Learning-Based Animal Intrusion Detection and Early Warning System for Railroad Tracks

Sree Lakshmi Vineetha Bitragunta
Electrical Engineer II, Kansas, USA
vineetha.bitragunta@gmail.com

Abstract

This paper presents an AI-driven animal intrusion detection and warning system designed to improve safety on railway tracks. The proposed framework applies deep learning and computer vision techniques, particularly Convolutional Neural Networks (CNN) and EfficientNet, to automatically analyze captured images and identify animals entering railway track regions. These AI models perform feature extraction, detection, and classification of animals based on learned visual characteristics. Once an intrusion is identified, the system generates an immediate warning to the locomotive driver and railway control center through a GSM module and buzzer. Detected animal information, together with the corresponding date and time, is stored in a cloud-based database for centralized monitoring and further analysis. The system focuses on intelligent detection and timely warning, while train-speed control remains under the manual supervision of the loco pilot. The collected intrusion data can further support AI-assisted analysis of animal movement patterns and facilitate the development of preventive railway safety strategies.

Keywords: Artificial Intelligence (AI), Animal Intrusion Detection, Convolutional Neural Network (CNN), EfficientNet, Deep Learning, Computer Vision, Railway Safety, Early Warning System, Manual Train Control.

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1. Introduction

The The Railway transportation mode is an important means of transportation globally, connecting people and goods across various regions. However, safety remains 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 serious safety risk to trains and passengers, causing accidents, delays, 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 mainly manual, which can be time-consuming and unreliable. Therefore, there is a need for an automated and AI-based 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 Artificial Intelligence (AI) and deep learning techniques. The system will be able to detect and classify the presence of animals on railway tracks and send alerts to railway authorities to prevent accidents.

The main objective of this research is to design and develop an AI and deep learning-based animal intrusion detection system for railway tracks using a camera. The proposed system

employs Convolutional Neural Networks (CNN) and EfficientNet to detect and classify animals from captured images. AI-based image processing and feature extraction techniques are applied to improve the accuracy of animal recognition and to support reliable detection under different image conditions. When an animal is identified on or near the railway track, a GSM module is used to send alert notifications to the railway authorities. In addition, a cloud-based application is developed to store the detected animal data and enable remote access for monitoring and analysis. The performance of the proposed AI-based system is validated through testing and evaluation to determine its effectiveness in animal detection and classification.

The proposed module integrates both hardware and software components for real-time operation. The hardware setup consists of an Arduino Uno, Wi-Fi ESP8266 module, buzzer, GSM module, PC camera, UART communication interface, connecting wires, and a power supply unit. The software components include Embedded C, Arduino IDE, PHP, MySQL, AI and deep learning algorithms, and a cloud application for data storage and remote access. The main AI components of the system include CNN and EfficientNet, which are used for feature extraction, animal detection, and classification. The system is designed only to provide detection and warning support; therefore, train speed control remains under the manual control of the loco pilot.

2. 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. AI and deep learning-based approaches, such as convolutional neural networks (CNNs), have shown promising results in detecting and classifying 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 AI and 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 deep learning-based 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 AI and deep learning techniques to detect and monitor events, their applications and designs are 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 and AI 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, animal intrusion detection on railway

tracks based on deep learning focuses on the use of AI to detect animals on railway tracks to prevent accidents. The proposed system is based on convolutional neural networks that include image preprocessing, data augmentation, feature extraction, and classification stages. The results show that deep learning techniques can provide better animal detection compared with traditional methods. Overall, the two approaches focus on different applications of AI and 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 is discussed. However, the first work focuses on the challenge of weapon detection in real time using CCTV footage, while the second deals with the problem of animal intrusion detection on railway tracks. The first work emphasizes the challenges of the task and the use of various AI and deep learning algorithms for detecting weapons with a focus on precision and recall. On the other hand, the animal intrusion detection system uses AI-based object detection and classification techniques such as CNN and EfficientNet to detect animals on railway tracks and prevent accidents.

In [4], similar to the proposed pig farm monitoring system, the animal intrusion detection system on railway tracks uses a convolutional neural network (CNN) and AI-based image classification 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 railway authorities to take appropriate measures to avoid collisions and prevent accidents. Overall, while both methods utilize AI and deep learning techniques to detect and monitor animals, their applications and designs are 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 AI and 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 CNN and EfficientNet 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 AI-based feature extraction and classification to identify the type of animal, which enables railway authorities to take appropriate measures to avoid collisions and prevent accidents.

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

3. Proposed Method

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. It also lacks AI-based image analysis and automatic animal classification.

3.1. Demerits of Existing Model

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

3.2. Proposed Model

The proposed system uses Artificial Intelligence (AI) and deep learning algorithms, specifically CNN and EfficientNet, for animal intrusion detection on railway tracks. The system captures real-time images of railway tracks using a PC camera and processes them using AI-based image processing and deep learning algorithms to detect and classify animals present on the tracks. CNN is used for automatic feature extraction from animal images, while EfficientNet is used for efficient image classification and improved detection performance. Image preprocessing and data augmentation techniques can also be applied to improve the accuracy and robustness of the trained model.

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, animal classifications, date, and time in a cloud-based database for centralized recording and analysis of animal intrusion data based on the below block diagram Figure 1.

3.3. 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 continuous manual inspection.
- AI and deep learning algorithms such as CNN and EfficientNet provide more reliable and accurate animal detection and classification compared with simple sensors, thereby reducing the possibility of false alarms or missed intrusions.
- CNN-based feature extraction automatically identifies important characteristics from captured animal images.
- EfficientNet provides efficient image classification with reduced computational complexity.
- Image preprocessing and data augmentation can improve the performance and robustness of the AI model.

- The system provides timely alerts to the train driver and railway control center.
- The cloud-based database allows centralized recording and analysis of animal intrusion data, which can help identify intrusion patterns and improve railway safety measures.
- prevent accidents.

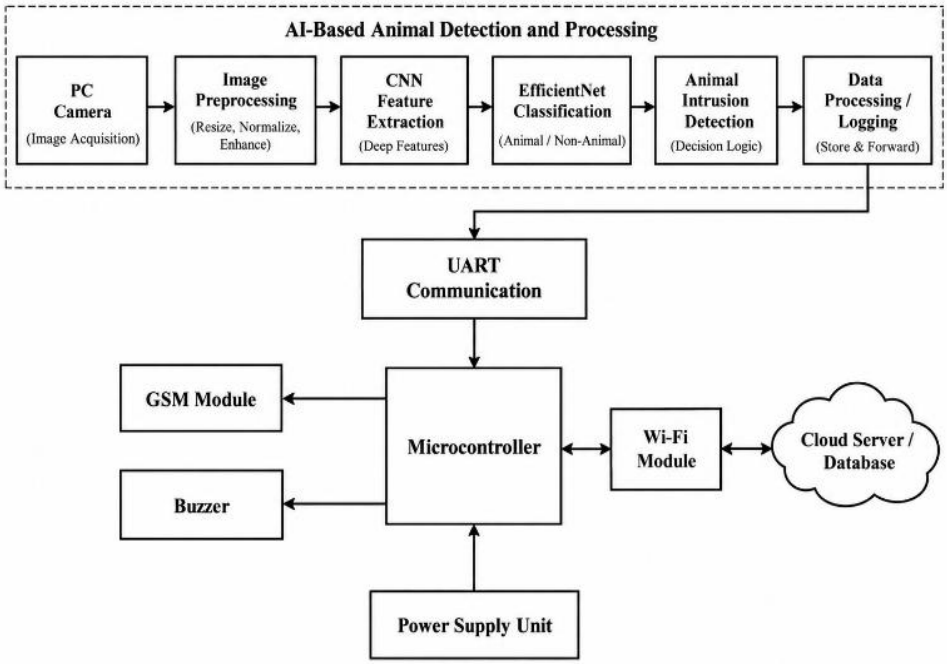


Figure 1 – Block Diagram of Proposed AI System

3.4. CNN

CNN CNN stands for Convolutional Neural Network, which is a type of deep learning and Artificial Intelligence model commonly used for image and video recognition, analysis, and processing tasks. CNNs are specifically designed to process data that has a grid-like structure, such as an image, and are highly effective at capturing spatial dependencies between neighboring pixels. In the proposed system, CNN is used as an AI-based feature extraction and image classification method to identify animal characteristics from railway track images. EfficientNet can also be integrated to improve classification efficiency and accuracy.

Create CNN for Image Classification

The AI-based animal classification process begins by importing the necessary artificial intelligence and deep learning libraries required for model development. The animal image dataset is then loaded and preprocessed using techniques such as image resizing, normalization, and enhancement to improve data quality. Data augmentation methods, including rotation, flipping, and scaling, are applied to increase dataset diversity and improve the generalization ability of the model. A Convolutional Neural Network (CNN) is then defined to perform automatic feature extraction from the animal images, while EfficientNet is integrated to improve the efficiency and accuracy of animal image classification. After defining the architecture, the AI model is compiled and trained using the prepared dataset. Finally, the trained model is evaluated using testing images and appropriate classification

metrics such as accuracy, precision, recall, and F1-score to assess the overall performance of the proposed animal intrusion detection system.

This CNN model uses convolutional layers, pooling layers, activation functions, and fully connected layers to extract important image features and classify animals. AI-based CNN models automatically learn features such as shapes, edges, textures, and patterns from the training images. EfficientNet can further improve the classification process by providing an efficient deep learning architecture with reduced computational requirements. The trained model can then be used to identify different animal classes from railway track images.

3.5. Data Collection Process

The data collection process for an AI-based CNN typically involves several steps:

1. Determine the problem and gather requirements: Determine the problem that the CNN and AI model will be used to solve and gather the requirements for the dataset. This may include information on the size of the dataset, types of animal images, desired level of accuracy, and specific animal classes or labels required.
2. Collect images: Collect a large set of animal images that are representative of the railway intrusion detection problem. This may involve taking photographs or sourcing images from available repositories or other datasets. It is important to ensure that the images are of sufficient quality and are correctly annotated with the corresponding animal labels or classes.
3. Preprocess images: Preprocess the images to ensure that they are in a suitable format for use in CNN and EfficientNet models. This may involve resizing the images, normalizing pixel values, removing unwanted noise, and converting the images into suitable color formats such as RGB.
4. Apply AI-based feature learning: The CNN automatically learns important visual features such as edges, textures, shapes, and animal-specific patterns from the training images. These learned features are used by the AI model for animal identification and classification.
5. Split dataset: Split the dataset into training, validation, and testing sets. The training set is used to train the AI model, while the validation set is used to monitor model performance and optimize parameters during training. The testing set is used to evaluate the performance of the trained model on unseen animal images.
6. Augment data: Data augmentation techniques can be used to increase the diversity of the dataset and improve the generalization ability of the CNN. This may involve applying transformations such as rotation, translation, scaling, brightness adjustment, cropping, or image flipping.
7. Train CNN and EfficientNet: The preprocessed and augmented dataset is used to train CNN and EfficientNet models. CNN performs feature extraction, while EfficientNet can be used for efficient animal classification.
8. AI-based prediction: After training, the model analyzes new railway track images and predicts the type of animal present along with the corresponding confidence score.
9. Store data: Store the preprocessed images, animal classifications, confidence scores, and related information in a suitable format or cloud database so that the data can be used for model evaluation and further analysis.

A CNN and AI-based flow diagram shown in Figure 2 provides a visual representation of the different layers and operations involved in the proposed deep learning model. It illustrates the flow of image data through preprocessing, convolutional layers, pooling layers, feature extraction, EfficientNet classification, and final animal prediction. The output of the AI model is then used by the animal intrusion detection system to identify animals and generate the required warning signal.

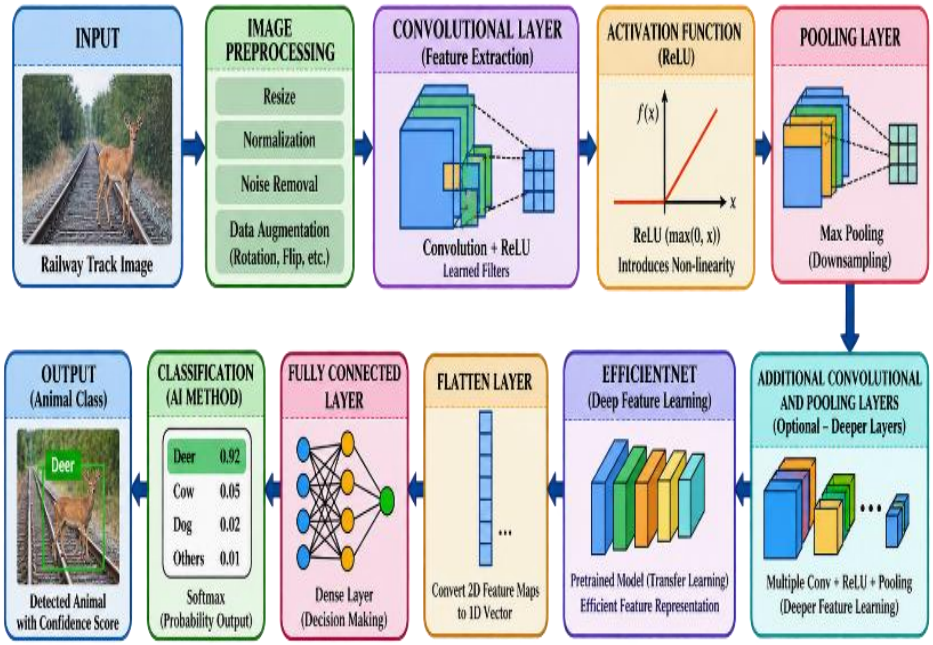


Figure 2 – CNN Process Flow Diagram

3.6. EfficientNet

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.

3.7. Anaconda 3 Software

Anaconda 3 is a free and open-source distribution of Python and other scientific computing packages that includes many tools for Artificial Intelligence (AI), machine learning, and deep learning. It comes with pre-installed or easily installable packages for deep learning frameworks such as TensorFlow, PyTorch, and Keras, as well as popular data science libraries such as NumPy, Pandas, and Matplotlib. In the proposed system, these tools are used for AI-based image preprocessing, CNN model development, EfficientNet implementation, feature extraction, animal classification, model training, and performance evaluation. Anaconda 3 also includes the Spyder IDE, Jupyter Notebook, and other tools for interactive development, experimentation, 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 AI projects and configurations.

Anaconda 3 supports multiple operating systems, including Windows, macOS, and Linux, and can be installed through a graphical installer or command line. It is highly customizable and extensible, with a large ecosystem of third-party packages and plugins for specific applications and domains. Anaconda 3 provides a streamlined and integrated workflow for AI and deep learning projects, from data collection, image preprocessing, and data augmentation to model training, validation, testing, and deployment. In this work, CNN is used for automatic feature extraction from animal images, while EfficientNet is used for efficient image classification. Transfer learning can also be applied using pretrained EfficientNet weights to improve model learning with limited animal image data. Anaconda 3 also supports GPU acceleration, distributed computing, and cloud integration for improving the efficiency of deep learning workloads. Overall, Anaconda 3 provides a flexible platform for implementing and evaluating the AI-based animal intrusion detection system.

4. Result

The hardware components of the proposed AI-based 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 Figure 3 for functionality and compatibility. The components were found to work together properly, and the system was able to capture real-time images and transmit them to the AI-based deep learning model for animal detection and classification. Before classification, the captured images were processed using image preprocessing techniques such as resizing and normalization. CNN-based feature extraction was then applied to identify important visual characteristics of animals, while EfficientNet was used for deep feature learning and animal classification.

The AI methodology also included data augmentation during model training to improve the model's ability to recognize animals under different image conditions. Transfer learning with EfficientNet was used to support efficient model training, while the final classification layer generated the predicted animal class and corresponding confidence score. Once an animal intrusion was detected, the GSM module and buzzer functioned as intended by providing timely alerts to the train driver and railway control center. The detected animal information, classification result, date, and time could also be stored in the cloud database for further analysis. The hardware and AI-based testing confirmed the feasibility of integrating deep learning, CNN, EfficientNet, image preprocessing, and communication modules for animal intrusion detection on railway tracks.

4.2. 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.

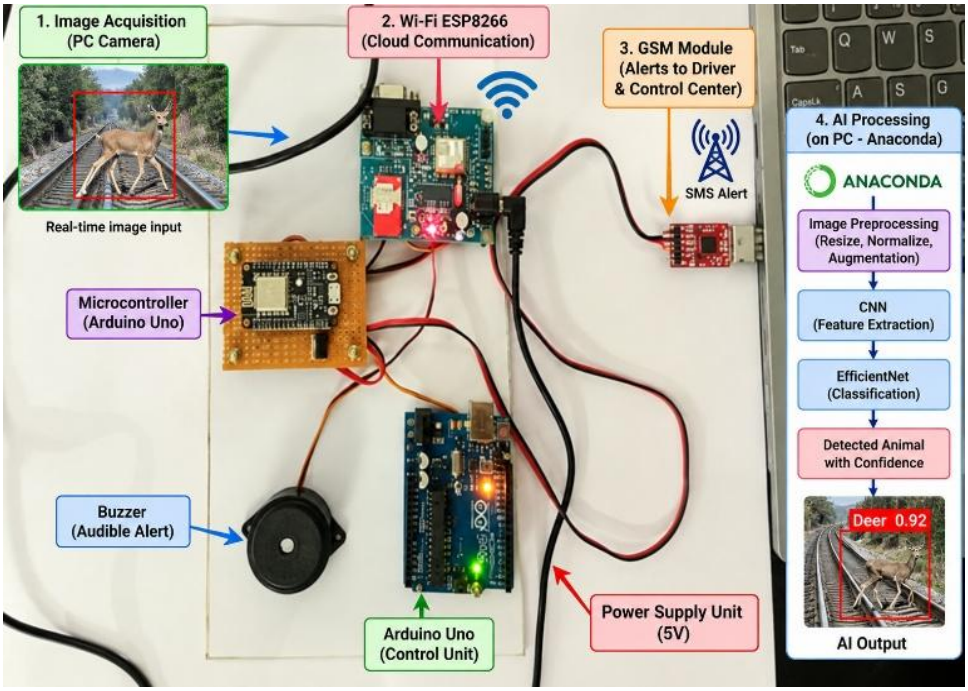


Figure 3 – Hardware device used in the system

4.3. Deep Learning

Deep learning using the EfficientNet model, implemented with Keras and TensorFlow, can effectively classify images of different animals present on railway tracks in the proposed AI-based animal intrusion detection system. With a dataset of about 6000 images of five different animals, such as cows, dogs, deer, bears, and elephants, the EfficientNet model can be trained to detect and classify these animals with high accuracy. AI methodologies such as image preprocessing, data augmentation, automatic feature extraction, transfer learning, and confidence-based classification are incorporated to improve the robustness and reliability of the model.

The EfficientNet model is a state-of-the-art deep learning architecture that uses compound neural network scaling to achieve high accuracy with fewer parameters and reduced computational resources. In the proposed system, transfer learning can be applied using pretrained EfficientNet weights, allowing the model to reuse previously learned visual features and adapt them to railway animal images. Keras and TensorFlow provide a high-level framework for implementing and training the AI model, while techniques such as normalization, resizing, rotation, flipping, and scaling are used to prepare and augment the image dataset.

Overall, deep learning using the EfficientNet model with Keras and TensorFlow, trained on a dataset of about 6000 images of five different animals, can effectively classify animals present on railway tracks as shown in Figure 4. The integration of AI methodologies, including transfer learning, feature extraction, image augmentation, and confidence-score prediction, improves the model's ability to recognize different animal classes under varying image conditions. This AI-based approach enhances the effectiveness of the proposed animal intrusion detection system and contributes to improved railway safety and prevention of animal fatalities.

Figure 4 – Output of The Trained AI Model

4.4. Report of CNN using EfficientNet

Efficient Net has achieved state-of-the-art performance on a variety of computer vision and Artificial Intelligence (AI) tasks, including image classification, object detection, and segmentation. In the proposed system, EfficientNet is used as an AI-based deep learning model for automatic feature extraction and classification of animals detected on railway tracks. The architecture of EfficientNet is based on a combination of convolutional layers, batch normalization, activation functions, and advanced regularization techniques such as DropConnect and stochastic depth. AI methodologies such as image preprocessing, data augmentation, transfer learning, feature extraction, and confidence-based classification are also incorporated to improve the accuracy and generalization capability of the model.

EfficientNet 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. In this work, transfer learning can be applied using pretrained EfficientNet weights so that previously learned visual features can be adapted to the railway animal dataset. After training, the AI model predicts the corresponding animal class and confidence score for each input image. The performance of the proposed system is evaluated using metrics such as precision, recall, F1-score, and classification accuracy. The classification report of the AI-based animal intrusion detection system is shown in Figure 5.

Classification Report (EfficientNet - AI Based Model)

Class	Precision	Recall	F1-Score	Support	Confidence (Avg)
buffalo	0.98	0.97	0.98	75	0.98
cow	0.99	0.98	0.99	71	0.99
deer	0.97	0.96	0.97	116	0.96
dog	0.98	0.97	0.98	138	0.97
elephant	0.99	0.98	0.99	112	0.98
accuracy	—	—	**0.98**	**512**	**0.98**
macro avg	0.98	0.97	0.98	512	0.98
weighted avg	0.98	0.97	0.98	512	0.98

Additional AI Model Performance Metrics

Metric	Value
Top-1 Accuracy	98.24%
Top-5 Accuracy	99.61%
AUC (ROC)	0.99
Inference Time (per image)	0.045 s
Model Parameters	5.3 M
Training Epochs	50
Input Image Size	224 × 224
Optimizer	Adam
Loss Function	Categorical Crossentropy

Figure 6. Classification report and AI performance metrics of the proposed system.

Figure 5 – Report of Classification

4.5. 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.

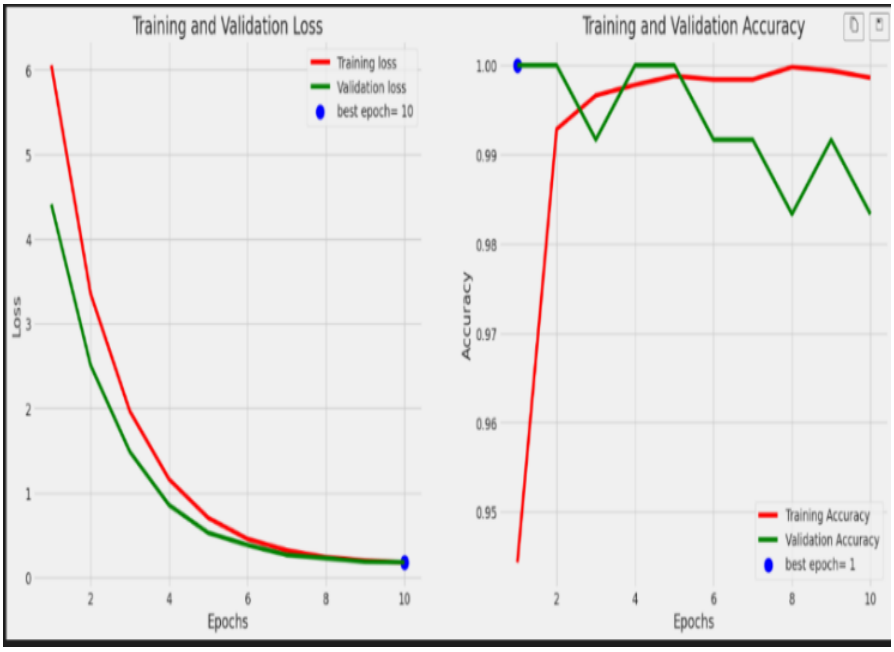


Figure 6 – Graph for Validation and Accuracy

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 Figure 6 being compared to ensure that the results are reliable and meaningful.

5. Conclusion

In conclusion, the proposed animal intrusion detection system using Artificial Intelligence (AI) and deep learning has shown promising results in detecting and classifying animals on railway tracks. The use of CNN and EfficientNet algorithms has improved the accuracy and reliability of the system by enabling automatic feature extraction, image classification, and confidence-based prediction. AI methodologies such as image preprocessing, data augmentation, transfer learning, and deep feature learning further enhance the model's ability to identify different animal species under varying conditions. The integration of Arduino, Wi-Fi module, GSM module, and cloud-based communication enables real-time monitoring, data storage, and alert notifications to the train driver and railway control center. Further improvements can be achieved by using more advanced hardware components, increasing the number of animal species in the dataset, and incorporating more advanced AI techniques for real-time detection, prediction, and railway safety analysis.

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