IOT BASED ANTI-POACHING SYSTEM FOR TREES AND WILDLIFE MONITORING SYSTEM IN REMOTE AREA

Mrs.shidule Komal Rajendra (komalshidule@gmail.com)
Prof.S.G Shinde
DEPARTMENT OF ELECTRONICS AND TELECOMMUNICATION
COLLEGE OF ENGINEERING, OSMANABAD.

Abstract- *The problem of illegal poaching and deforestation is a threat to biodiversity, resulting in the loss of wildlife and the destruction of the environment. In order to solve this problem, we recommend implementing an Anti-Poaching System using the Internet of Things (IoT). This system utilizes the Raspberry Pi microcontroller, which can transmit videos to the cloud server. To detect animals, a machine learning model is used to identify the animals and track their activities. This will allow wildlife conservationists to keep track of the animals' location and detect any abnormalities. Also, to detect fires, a You Only Look Once (YOLO) deep learning algorithm is used to detect wildfires as a result of any illegal activities, including poaching or deforestation. Any suspicious activity detected through the data collected, including people who are not supposed to be there, gunshot sounds, and fire, automatically triggers an alert. Alerts generated through the system can be transmitted to the forest authorities using a mobile app or web dashboard in order to ensure immediate action is taken. The technology has the capacity to use GPS to locate the exact position where any threat has been spotted. It can be observed that due to the implementation of such an intelligent forest surveillance system, forests can be protected in a better way.*

Keywords- *IoT, Anti-Poaching System, Real-Time Monitoring, Raspberry Pi, Machine Learning, YOLO, Fire Detection, Wildlife Conservation, Deep Learning, Video Surveillance, Illegal Poaching, Deforestation, Smart Surveillance, Threat Detection, Automated Alerts.*

I. INTRODUCTION

Poaching and deforestation have become some of the most significant threats to the conservation of wildlife and ecological balance. Species are on the brink of extinction due to unchecked poaching and destruction of their natural habitats, with deforestation speeding up global warming and loss of biodiversity. However, manual methods of monitoring the forests, including physical patrolling and surveillance through static camera systems, have been found inefficient because of the sheer size of the area covered by forests and the scarcity of manpower available for the purpose.

In this paper, we introduce an IoT Anti-Poaching System which utilizes Raspberry Pi for live video streaming, machine learning for recognizing animals, and YOLO (You Only Look Once) for fire detection. The Raspberry Pi is a compact computer that is low-cost and energy-efficient and hence provides live video capturing capabilities, and the live video stream is analyzed using a cloud service. Using deep learning methods, the proposed system will be able to differentiate between normal behavior and abnormal behavior, identifying any signs of poaching or forest fires.

The animal recognition module makes use of machine learning algorithms that are trained on wildlife data sets and capable of recognizing and categorizing different animals. This is important for tracking the migration of endangered animals and also for detecting poachers. Moreover, the fire detection module uses YOLO technology for detecting any fire outbreak due to poacher camps or forest destruction fires. This helps the forest authorities to take preventive measures at the earliest to prevent any kind of environmental damage.

When the system detects any kind of suspicious activity, it automatically sends out alerts. The alerts are sent to the forest officials through the mobile app or web portal, with video footage, location coordinates, and timestamps attached to the alerts. This helps to expedite response time and allow officials to deploy patrol teams to the area. Moreover, gunshot detection can be incorporated into the system to increase its effectiveness against poaching activities.

By leveraging the Internet of Things, artificial intelligence, and real-time data analysis, this system provides a novel and scalable solution to wildlife conservation and forestry preservation. With the deployment of this automated monitoring system, there will be a dramatic decline in poaching cases, illegal deforestation, and overall global conservation initiatives. The main objective of this study is to illustrate how the combination of deep learning and Internet of Things technology could benefit environmental conservation efforts.

II. RELATED WORK

In this paper, an innovative IoT-based wildlife monitoring system has been developed, which includes sensors and other devices that help in measuring various environmental and animal movement parameters in real-time. It is shown how the system measures habitat variations and offers valuable information to wildlife conservation efforts through the use of environmental sensors and GPS. The results reveal that the system greatly improves the capability of identifying and dealing with any cases of poaching, thereby helping in managing wildlife reserves. [1]

In this article, the authors consider different approaches to the use of machine learning algorithms aimed at identifying poaching cases. The effectiveness of such methods as random forest algorithms, support vector machines, and even deep learning models is considered. As a result, the study demonstrates how machine learning can greatly help poaching predictions and resource allocation in the fight against poachers. [2]

This paper examines the use of drones with camera and sensor capabilities for observing wildlife reserves for cases of poaching. The authors have developed a framework employing computer vision technology to detect any abnormal human behavior on aerial images. Examples show how the use of drones could easily detect cases of poaching in a short time, enabling wildlife agencies to take action immediately. The findings indicate that the use of drones could serve as an effective approach in supporting species conservation programs.[3]

The present paper examines the process of creating a mobile application that can be used to monitor wildlife activities among the local communities. The importance of involving local communities in conservation programs is explained by making them capable of reporting any poaching activities within their immediate environment using the application. The study indicates that the application has helped in increasing public awareness about wildlife conservation programs. [4]

In this paper, the authors suggest an intelligent solution based on IoT devices and AI technologies to boost the performance of wildlife management programs. Their model incorporates smart cameras and environmental sensors that gather information related to the number of wildlife and human activities. The paper describes how AI systems utilize this information to identify any threat that could affect wildlife, including poaching and habitat loss. The authors' findings show that this technology integration could effectively optimize the decision-making process in conservation management. [5]

This review paper explores different uses of AI technology in the context of animal conservation, with particular emphasis placed on applications associated with monitoring the environment and stopping poaching. In this study, the authors examine the effectiveness of AI technology in terms of detecting illegal activities and analyzing the condition of an ecosystem. This research highlights the possibilities that AI technology offers for improving animal conservation practices, but the importance of further development is stressed. [6]

This research paper explores an IoT-based antipoaching solution that monitors protected areas and detects any illegal activity. The researchers describe the structure of the system in detail, highlighting its components such as cameras, sensors, and the central monitoring system. The research findings reveal that the proposed solution greatly enhances response time through immediate alerts to park rangers on any suspicious activities. [7]

This paper discusses the application of video analytics techniques for observing animals and determining the presence of poachers. The authors have offered several approaches to analyzing the footage from trail cameras, which allows for automatic detection of any intrusion made by people and species classification of animals. The findings demonstrate that video analytics can save considerable time and effort in observing animals. [8]

This paper examines the possibilities for using technology to encourage community involvement in the efforts of wildlife conservation. The researchers present examples demonstrating how communities could play a role in reporting cases of poaching as well as disseminating information on wildlife conservation via social networking sites and mobile applications. [9]

The authors of the review discuss the potential benefits and obstacles connected with the introduction of the IoT technologies in wildlife conservation. Some of the issues that they mention include data management, rural area connectivity, and interdisciplinary collaboration. As far as examples go, the report provides information about cases when the IoT technologies were successfully implemented in wildlife conservation. [10]

III. PROPOSED SYSTEM

The proposed anti-poaching system based on the Internet of Things technology will ensure proper surveillance and protection of natural resources like animals and forests in the respective areas for addressing the problem of poaching and unauthorized felling of trees. The system will consist of cameras and sensors deployed across the specified region. Acoustic sensors will be used to detect the sound of gunfire, and chainsaws, while motion sensors will detect any illegal movement. Other sensors include the environmental sensors that detect environmental parameters such as temperature and humidity to indicate fire hazards. The cameras used have high-resolution to ensure effective capturing of images and videos, and infrared cameras can detect heat to enable night-time surveillance. The captured data is transmitted to the server using reliable communication devices like ESP32, which can ensure connectivity regardless of the location. The server has to collect and analyze the data using smart machine learning algorithms that detect suspicious movements.

Proposed Architecture:

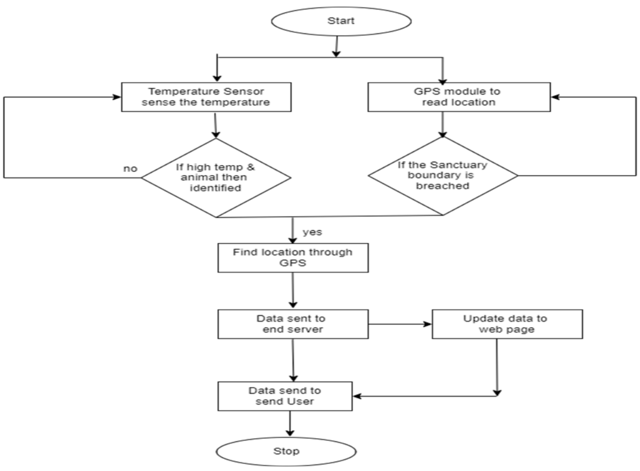


Fig.1. Proposed Architecture

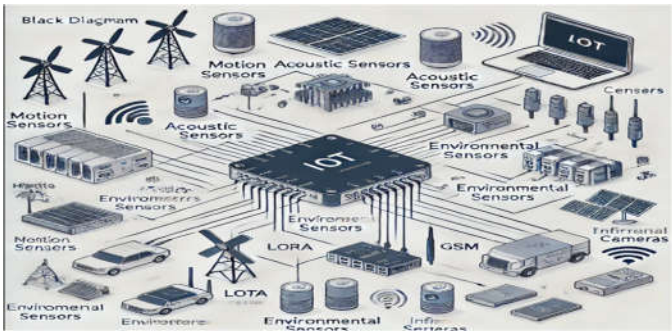


Figure2 Framework Diagram

CNN Model

Convolutional neural networks (CNNs) are commonly applied in image and object recognition, thus they can be perfectly applied to perform animal detection in real time in forest areas. This work proposes an animal detection approach using a CNN model that is used to detect different animals using video images taken by the Raspberry Pi cameras. The CNN model contains several layers such as convolutional layers and pooling layers for classification purposes. This model analyzes images by identifying key attributes, including edge detection, texture, and pattern recognition, thus allowing precise recognition of animals in their native environment. In the case of our CNN model, the input data is presented in the form of images that have been adjusted to a uniform size, typically 224x224 pixels, and normalization has been performed to make the analysis more effective. In the first stages of the algorithm, convolutional layers extract information about spatial structures in images, while rectified linear units (ReLUs) create nonlinear features. For greater efficiency, max pooling layers downsample feature maps. Afterward, features are transferred to fully connected layers. The output layer utilizes the softmax function to classify the most probable animal type. To achieve maximum accuracy, the CNN model will undergo training on a large-scale dataset of animal pictures, which may incorporate public data such as ImageNet or naturalist data or proprietary data gathered through surveillance cameras. During training, techniques such as flipping, rotating, zooming, and brightness will be employed to enhance the performance of the model. Moreover, normalization will be performed by scaling pixel values between 0 and 1 while one-hot encoding will be implemented to transform classes into numerical format. The model will be optimized by the Adam optimizer with the categorical cross-entropy loss function, leading to faster and more accurate training. After the completion of training, the CNN model will be executed on the Raspberry Pi platform for real-time monitoring and identification of wild animals. Raspberry Pi will capture videos and analyze animal types in each frame based on the predictions made by the CNN model using the trained weights. In case there is any animal spotted, then real-time alerts can be sent to the concerned forest officials through a mobile app or even a web interface. Such alerts will facilitate faster reaction by forest officials who will take action to prevent any form of poaching and other forms of illegal activities. To conclude, CNN-powered animal detection is of great significance in wildlife conservation as well as poaching prevention efforts. Through the combination of deep learning and IoT technologies, this technology serves as a viable solution for monitoring forest areas in real time. Some possible upgrades to this technology would be implementing features such as object tracking, sound recognition and the integration with thermal cameras among others.

YOLO Model

The You Only Look Once (YOLO) algorithm is a high-speed object detection technique suitable for detecting fires in forests. It is employed in this case study to detect fires through video feeds obtained from the Raspberry Pi cameras and consequently initiate measures aimed at preventing forest fires from spreading. The efficiency of the YOLO algorithm is attributed to its use of a single-stage detection process. This feature enables it to detect fires efficiently from real-time video feeds. In detecting fire using the YOLO model, video feeds are processed by first dividing them into a grid system. Within the grid system, each cell predicts the position of several objects using bounding boxes alongside a confidence level. With regard to fire detection, the YOLO model uses features such as flames and smoke to detect a fire incident. Instead of relying on changes in the intensity of pixels, the YOLO model detects fire based on its feature detection capability. Training Data Set for Fire Detection by YOLO is comprised of images having multiple fire scenarios, smoke, and non-fire situations, providing maximum accuracy levels. Training data can be acquired from public sources such as Flame Dataset and FireNet Dataset. Images are annotated with bounding boxes covering fire areas, and the loss function is used to train the model while reducing any possible localization error and false positive issues. Data augmentation like adjusting brightness, adding noise, and rotating the image are some of the methods to enhance accuracy levels despite changes in the environment. After training the model, YOLO is installed on a Raspberry Pi machine using OpenCV and TensorFlow or Darknet to analyze video feeds in real time. The YOLO model scans frames constantly, detecting fire breakout in milliseconds. Once a fire outbreak is detected, alerts are raised to forest officers or firefighters through SMS or mobile applications. Moreover, an automatic response mechanism could be added for triggering fire suppression measures like water sprinklers and fire-retardant barriers in hazardous areas.

YOLO fire detection system is a quick and precise method that will help avoid fires in forested regions. This fire detection system using deep learning and IoT technology offers a great advantage for instant fire hazard monitoring and response. Future advancements for this fire detection model might involve thermal imaging systems, drone fire monitoring, and AI-based risk analysis among others.

A Raspberry Pi Zero is a low-cost and small-sized microcontroller which can be used for capturing video in real-time as well as uploading to the cloud storage in IoT-based anti-poaching and fire detection applications. With an attached Raspberry Pi Camera Module, it can capture video streams and send them to a server or any cloud storage system where processing can take place using algorithms like CNN and YOLO.

1. Hardware Setup

The setup consists of:

Raspberry Pi Zero (W/WH) – A lightweight microcontroller with Wi-Fi support.

Raspberry Pi Camera Module – A compatible camera for capturing video (e.g., Raspberry Pi Camera v2 or NoIR for night vision).

MicroSD Card – Stores the operating system and required software.

Power Supply (5V, 2A) – Provides stable power to the Raspberry Pi Zero.

Figure 3 Zero Raspberry PI

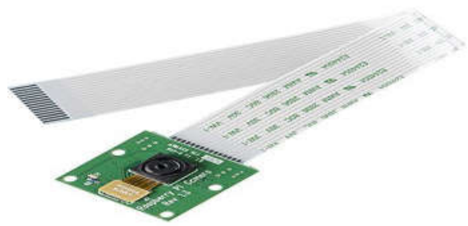


Figure 4 Raspberry PI Camera Module

Raspberry Pi Camera Module is a small high-resolution camera used for taking images and recording videos through Raspberry Pi. It is linked to the CSI (Camera Serial Interface) port of the Raspberry Pi, which facilitates high-speed data transmission. This camera module is vital in IoT-based anti-poaching and fire detection applications where video surveillance, monitoring, and fire or animal detection are done using artificial intelligence.

1.Result and discussion

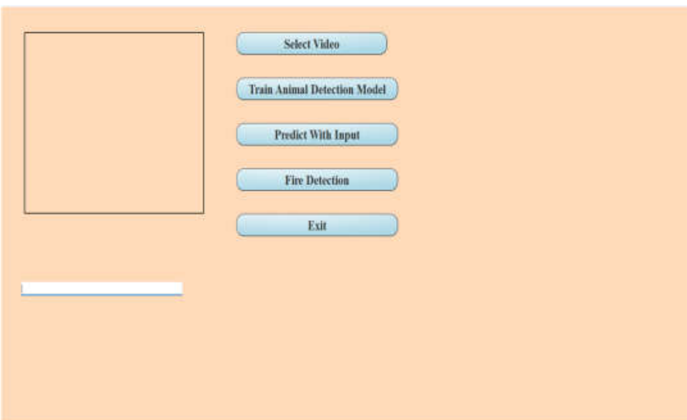


Figure 5 Main UI Part

The figure 5 shows the main UI part where user can select the video, train the model and predict animal and fire.

2. CNN Model Accuracy Training and validation

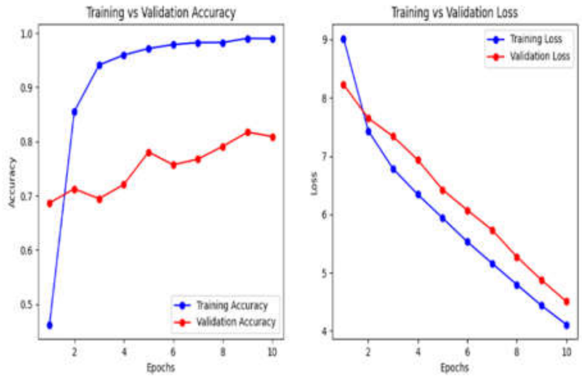


Figure 6 Training VS Validation Accuracy

The graph figure 6 includes two graphs: Training vs. Validation Accuracy graph and Training vs. Validation Loss graph. The graph shows the results of a machine learning algorithm, probably a CNN algorithm, throughout 10 epochs. As for the Training vs. Validation Accuracy graph, there is a sharp increase in the training accuracy (blue line) and a steady increase in the validation accuracy (red line) until the 5th epoch, when the training accuracy reaches about 100%, whereas the validation accuracy is still about 70%. Then after the 10th epoch, the validation accuracy reaches a maximum of about 80%. Hence, there might be an issue of overfitting, as the accuracy of the validation set is lower compared to the accuracy of the training set. On the other hand, in the Training vs. Validation Loss graph, the model successfully learns the process until the 10th epoch because there is a reduction in both values.

In general, although the learning of the model is excellent, there is still some disparity in accuracy and loss, indicating that further optimization, such as regularization or dropout, can improve the ability of generalization of the model to unseen data.

3. Confusion Matrix

The classification outcome of the proposed CNN model is an indicator of its accuracy and other metrics. The CNN model gives an accuracy score of 90% based on the comparison between actual and predicted outcomes. Accuracy score is obtained using the following formula:

$$\text{Accuracy} = TP + TN/TP + TN + FP + FN$$

Precision: It can be characterized by the number of accurate predictions made by the model or the percentage of all the positive classes that the model predicted correctly. The precision of the above graph is 70%. It can be calculated using the following formula:

$$\text{"Precision"} = TP/(TP+FP)$$

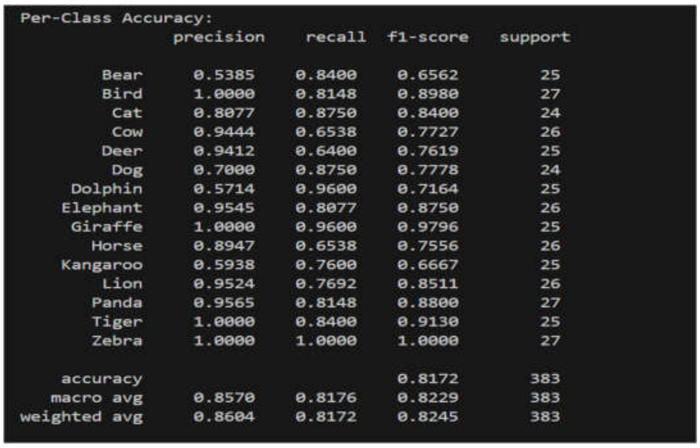
Recall: It is mentioned as the number of positive classes that the model predicted correctly out of the total number of positive classes. The recall must be as large as possible. The proposed system has a recall value of 0.67%.

"Recall" = TP/(TP+FN)

F1-Score: The F1-score is defined as the harmonic mean between the two measures, precision, and recall. It is suitable in cases where there is an imbalance between the number of samples in each class of a dataset. The F1-score of this CNN model is 0.72, calculated as:

$$F1S\text{ core } = 2 \times \left(\frac{\text{Precision } \times \text{ Recall}}{\text{Precision } + \text{ Recall}}\right)$$

These performance measures are important in determining how efficient the CNN classifier is. Even though the CNN model exhibits high precision, its recall indicates that it can still improve in terms of detecting positive samples.



Per-Class Accuracy:

	precision	recall	f1-score	support
Bear	0.5385	0.8400	0.6562	25
Bird	1.0000	0.8148	0.8980	27
Cat	0.8077	0.8750	0.8400	24
Cow	0.9444	0.6538	0.7727	26
Deer	0.9412	0.6400	0.7619	25
Dog	0.7000	0.8750	0.7778	24
Dolphin	0.5714	0.9600	0.7164	25
Elephant	0.9545	0.8077	0.8750	26
Giraffe	1.0000	0.9600	0.9796	25
Horse	0.8947	0.6538	0.7556	26
Kangaroo	0.5938	0.7600	0.6667	25
Lion	0.9524	0.7692	0.8511	26
Panda	0.9565	0.8148	0.8800	27
Tiger	1.0000	0.8400	0.9130	25
Zebra	1.0000	1.0000	1.0000	27
accuracy			0.8172	383
macro avg	0.8570	0.8176	0.8229	383
weighted avg	0.8604	0.8172	0.8245	383

Figure 7 Confusion matrix

The classification report shown in figure 7 depicts the precision, recall, f1-score, and support for various categories of animals from the model used. Every row in the table represents a single class and shows the level of effectiveness of the model in predicting those classes. The accuracy refers to the percentage of correctly predicted instances within each class prediction, while the recall indicates the percentage of actual instances within each class that the model captures. The model works very effectively on certain classes including "Bird," "Giraffe," "Tiger," and "Zebra," scoring perfectly in both precision and recall values, but classes such as "Bear" and "Kangaroo" score relatively poorly, implying that there are difficulties in the classifications process. The accuracy of the model stands at 81.72%. This can also be said for macro average and weighted average, which stand at very high levels.

Figure 8 Animal Detection

The figure 8 shows the animal detection. When the animal is detected the system buzzer is on.

4. Fire Detection

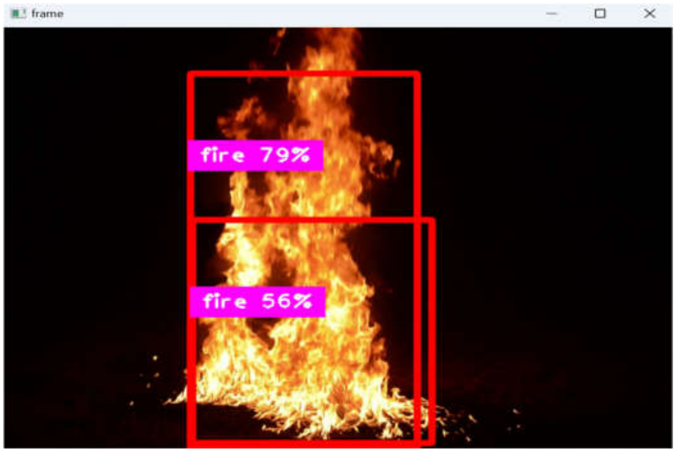


Figure 9 Fire Detection

The figure9 shows the fire detection from inputted video. When the fire is detected the system buzzer is on.

5. Accuracy Over Epoch

Table 1 Accuracy over epoch

Epoch	Accuracy
10	82.77 %
30	90.20 %
50	93.56 %

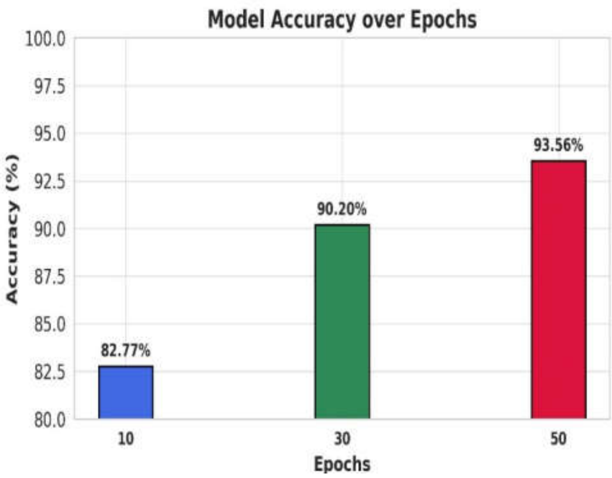


Figure10 Model Accuracy over epoch

Figure 10 shows the bar graph that displays the improvement in accuracy levels of a model through various epochs (10, 30, and 50). The x-axis depicts the various epochs, while the y-axis shows the respective accuracy percentage levels. It can be seen that there is a continuous increase in the accuracy levels from 82.77% at epoch 10, then to 90.20% at epoch 30, and finally to 93.56% at epoch 50. The bars are colored to improve visibility, and the numeric values are shown above each bar for better illustration.

Conclusion

A system based on the Internet of Things (IoT), such as the Anti-Poaching Activity Detection System, is an innovative technology that uses a real-time and intelligent approach towards protecting animals. This can be achieved through the use of Raspberry Pi with a camera module that allows video streaming, CNN machine learning models for detecting animals, and YOLO for fire detection. As a result, this system continuously monitors the protected areas. Cloud storage and real-time alerts, along with AI-based detection systems, allow the efficient functioning of the system in terms of detecting any suspicious activities in the protected areas. Thanks to the low-powered IoT sensors, remote monitoring, and automated notifications, it reduces human intervention, making its coverage maximum. Even though there are various benefits, it is also essential to consider certain difficulties that should be overcome to achieve maximum efficiency, which can be attributed to limited connectivity of the network in remote regions, false positive detections, as well as adequate energy consumption during continuous operation of the system. Improvements to this system might include edge AI processing, advanced detection algorithms, as well as drone integration.

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