Image Processing based Animal Intrusion Detection System in Agricultural Fields using Deep Learning

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IMAGE PROCESSING BASED ANIMAL INTRUSION DETECTION SYSTEM IN AGRICULTURAL FIELDS USING DEEP LEARNING

A PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

Agriculture is one of the most important industries in any economy since it plays a big role in the food supply chain. Agricultural fields, on the other hand, confront a number of issues, including animal encroachment, which can cause severe crop damage and loss. Traditional animal control tactics, such as electrical fences, physical barriers, and scarecrows, can be inefficient, time-consuming and a serious threat to animal lives. The animals either become entangled in the fence's wire mesh or were electrocuted by the electric lines. To overcome these problems we propose a unique method that involves image processing-based animal incursion detection system in agricultural fields using Raspberry Pi and deep learning technique, mainly the YOLOv7. This technology captures live video feeds of agricultural fields using a camera and analyses them using deep learning algorithm to detect any animal invasions. If an intrusion is detected, the system emits specific repellent sounds for specific animal via speakers in order to scare them away and alerts the farmers by sending SMS. This method provides an efficient and practical alternative for crop damage prevention and human-wildlife conflict reduction in agricultural settings.

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AIDSAF	Animal Intrusion Detection System in Agricultural Fields
YOLO	You Only Look Once
RCNN	Regions with Convolutional Neural Networks
DL	Deep Learning
ML	Machine Learning
SMS	Short Message Service
MAP	Mean Average Precision
CPU	Central Processing Unit
IoT	Internet of Things
Wifi	Wireless Fidelity
SSD	Single Shot Detector
LED	Light Emitting Diode
LOS	Line of Sight
PIR	Passive Infrared Sensor
GPU	Graphics Processing Unit
HDMI	High-Definition Multimedia Interface
M2M	Machine to Machine
RPN	Region Proposal Network
OpenCV	Open-Source Computer Vision Library

CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Agriculture is the primary source of income for many people in many parts of the world [5]. Human-wildlife conflict refers to interaction between wild animals and people and resultant negative impact on people or their resources, or wild animals or their habitat. In India, common causes of wildlife death include fencing and electrocution. Fencing is used to keep wildlife out of agricultural areas and human communities, while electric barriers keep elephants out of human populations. In 2014, a research published in the journal Oryx looked at the effect of fencing on animal mortality in India's Kanha National Park. Fencing was shown to be responsible for the deaths of various large species, including tigers, leopards, elephants, and gaurs, according to the study. Traditional agricultural methods are ineffective, and employing guards to keep an eye on crops and keep animals at away is not a viable option [3]. However, these measures may unintentionally harm wildlife, with serious ecological and conservation consequences.

A study published in 2017 in the journal PLOS One looked at the effect of electric fencing on elephant death in India. According to the research, electrocution from these fences was the top cause of elephant death in the nation, killing almost 400 elephants between 2000 and 2013. The study also discovered that using solar-powered fences lowered the frequency of elephant fatalities, indicating that alternate technologies might offset the detrimental impact of electric barriers on animals. Farmers typically employ electrical fences to safeguard their fields from animals whose electrocution with cramp causes them to behave abnormally [4].

Reports in figure 1.1 shows that the death of human lives have been significantly increased and also leading to heavy crop damage. Fig 1.1 depicts the number of human kills, injuries, cattle kills and crop damage from year 2017 to 2022.

CALL OF THE WILD

Year	Human kills	Injuries	Cattle kills	Crop damage
2017	53	686	5,961	37,971
2018	50	349	8,311	38,347
2019	36	299	9,258	37,971
2020	47	412	9,139	38,347
2021	83	553	10,317	56,402
2022	94	472	6,965	27,183

Figure 1.1 Deaths due to human wildlife conflicts

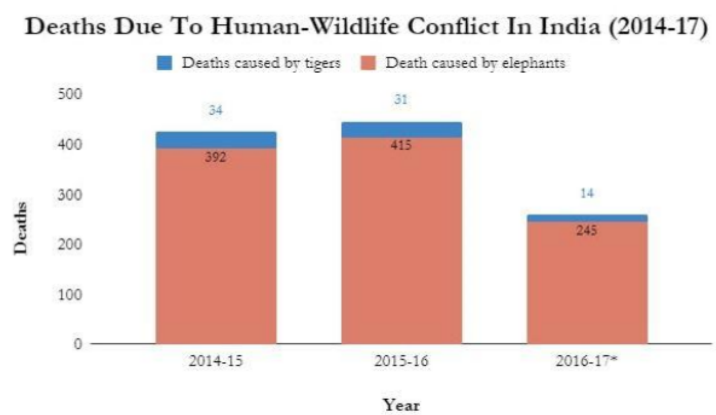

Figure 1.2 Statistical representation

According to data from figure 1.2, the Ministry of Environment, Forests and Climate Change, from the above figure we can conclude that the conflict with wild animals (mostly elephants and tigers), has killed more than 1,100 people across India between 2014 and 2017. During the period, 1,052 lives were lost to elephants. Among states, West Bengal led the list with 266 deaths (25%) and was followed by Jharkhand and Chhattisgarh. 92 people died in tiger attacks. Of these, 32 were in West Bengal alone, followed by Maharashtra and Madhya Pradesh.

Human wildlife conflicts have been in existence for ages as long as wild animals and people shared the same landscape and resources. Development activities cause more interference in the forest, the privacy of wildlife and these ultimately cause conflict between humans and wildlife for survival. Recently the incidents of human-wildlife conflict have increased considerably, and it had negative impacts on humans- social, economic, and cultural life, conservation of wildlife populations, and on the environment. Man-animal conflict often takes place when wild animals cause damage to crops and property, killing livestock and injuring human beings. Thus, the conflicts between wildlife and humans threaten livelihoods, cost many lives, both humans and wildlife. The major reason for the wild animal attack is afforestation, increasing population and the conflict for common resource base.

Agricultural fields face several challenges, including animal intrusion, which can result in significant crop damage and loss. Traditional methods of animal control, such as fencing and scarecrows, can be ineffective and time-consuming. This project proposes an image processing-based animal intrusion detection system using Raspberry Pi model in agricultural fields by using deep learning algorithms such as YOLOv7 and Fast RCNN models. Deep learning-based image processing-based animal incursion detection systems, such as Yolov7 and Faster RCNN, have emerged as a possible answer to this problem. ML, together with IoT (Internet of Things) enabled farm gear, will be critical components of the next agricultural revolution [9].

These algorithms are commonly utilized in computer vision applications because of their excellent accuracy and quick processing time. IoT will present increased availability of gadgets, frameworks, and administrations that will pioneer machine-to-machine (M2M) collaborations and disseminate a broad range of conventions, spaces, and applications [5]. The main objective is to identify animals that are not allowed in a given region and alerting the owner or other designated person.

The system utilizes a webcam to capture live video feed of the agricultural fields, detects and analyzes the intrusion using Raspberry Pi and deep learning models. If an intrusion is detected, the system produces repellent sounds with help of buzzers and also sends an alert to farmers via GSM. AIDSAF provides an efficient and effective solution for preventing crop damage and reducing human-wildlife conflict in agricultural fields.

Figure 1.3 Animal intruding the cultivated crops

Figure 1.3 shows the animals creating harm to the cultivated crops. This type of behavior of animal cause heavy loss to the farmers as well as threat to animal lives.

This takes life of both animals and human beings. Forty people has lost their lives due to electric fence meant to ward Electric fences are mainly used to protect the crops from animal which is shown in figure 1.4. off elephants in Jhapa in nine years. Around 11 wild elephants have also died in this process. According to this report the electric fences cause the life of people nearby than that of elephants. So, this type of technique is very harmful.

Figure 1.4 Electric Fields to prevent incursion

The eventual aim is to build an enhanced world for human beings, where the objects around us recognize our desire and hence act accordingly without any precise instructions. IoT is a mixture of software and hardware technologies including embedded devices which allows offer facilities and services to anyone, anytime, anywhere using any network. The connectivity then helps us to obtain extra data from different places, confirming many ways to increase efficiency and progresses the security and safety.

Internet of Things is ground-breaking administrations that can help organizations to improve their presentation through examination and security to give better result. Organizations in the utilities, framework, oil and gas, transportation, protection, assembling, and retail areas can acquire the advantages of IoT by settling on more knowledgeable choices, helped by the spout of conditional and interactional information available to them.

IoT is going to propose higher availability of gadgets, frameworks, and administrations that ventures out in front of machine-to-machine (M2M) collaborations and spreads a wide scope of conventions, spaces, and applications.

Agriculture is the main source of occupation of several individuals around various portions of the world. Sadly, farmers are yet reliant on conventional methods that have developed several years back. Because of this the yield of harvests are getting low. Additionally, numerals of elements that add to the yield of harvests creature interruption is likewise one with them. In current years wild animals are specific test for the farmers everywhere on the world, animals like wild pigs, elephant, tiger and monkeys and so forth cause serious harm to crop by animals running over the field and stomp on over the harvests. It makes the budgetary issues for the farmers.

These findings emphasize the need for more study and attention to the issue of fence and electrocution in India. It is critical to comprehend the scope of the issue, as well as the influence of various types of fences and electrical technologies on animal death. This research can help to guide the development of more effective and environmentally sustainable wildlife-human conflict mitigation methods.

In addition to research, policy measures are required to solve the issue of fence and electrocution. The Indian government has taken steps such as paying farmers for agricultural loss caused by wildlife and subsidizing the building of solar-powered fences. More has to be done, however, to ensure that these policies are effective and equitable, and that they are administered in a way that considers the ecological and conservation consequences of wildlife-human conflict.

To summarize, fences and electrocution are major causes of animal death in India. More research is needed to determine the scope of the problem and to devise more effective and environmentally sustainable solutions to wildlife-human conflict. Simultaneously, policy interventions are required to ensure that these measures are effective, equitable, and take the ecological and conservation implications of wildlife-human conflict into account.

In this research, we present an image processing-based AIDSAF based on Yolov7 and Faster RCNN deep learning algorithms. We construct the system using the Raspberry Pi 4 model B, a low-cost and power-efficient computer, making it a cheap and accessible alternative for farmers. The suggested technology is predicted to drastically minimize crop damage caused by animal encroachment while also improving agricultural production's sustainability and productivity.

CHAPTER 2

LITERATURE REVIEW

[1] presents IoT technological improvements on the application layer in an understandable manner, together with the lightweight communication protocol lightweight M2M (LwM2M). The research [2] indicates that the biggest drawback is the slower computing efficiency and accuracy of CNN. [3] suggests that the YOLOv5 algorithm be used for real-time animal detection in precision agriculture. The authors employed a dataset of cows, buffaloes, and horses, and the YOLOv5 system detected animals with great accuracy. In terms of accuracy, YOLOv7 outperforms YOLOv5. On the COCO dataset, the MAP (mean average precision) for YOLOv5 is 55.0%, while for YOLov7, it is 56.8%. According to research, the adjustment resulted in a reduction of 35-40% parameters as well as half of the calculations for each (normal and embedded system).

The tests in [3] used a small dataset that may not be typical of all forms of animal invasions that farmers may face. In AIDSAF the train images used are 3000 which include 8 classes of animals namely cow, bear, elephant, bird, horse, sheep, cat, and dog. Total of 4000 images were used for training and testing the model on the whole. [4] goes through many strategies such as the Raspberry Pi CPU, WiFi module, R-CNN, SSD, and Twilio. SSD method outperforms R-CNN algorithm in terms of calculation time, accuracy, and efficiency.

[5] works by comparing the acquired image from the IoT model to the training dataset, splitting the image into frames, and then storing the data in the cloud, which maintains the other databases. 2 holds the identified object, and then the raspberry pi receives the data of item recognition and decides whether to activate the buzzer, LED lights, or both. Furthermore, when necessary, sends the notification to the client/ranch. [6] created a YOLOV3 model to identify the

animal in a user-supplied photograph and it takes longer to forecast the result, and we cannot choose our own pictures. The downside of [6] is that when we run the YOLO V3 model, it predicts right and inaccurate predictions, and it does not forecast for certain photographs and does not take input images correctly.

The primary concept of [8] is that in order to address this difficulty, an intelligent monitoring system that can automatically monitor and recognize the image of animal ingress and send an alarm message to humans is necessary. Attempts to boost recall through tracking and multi model pooling failed in [9]. RETINA and YOLO were demonstrated to be competitive with bigger models while being lightweight enough for multi-camera mobile deployment. Giordano and colleagues worked on and created an IoT application for crop security from animal encroachment in the agricultural field.

The idea in [10] employed wireless technology such as to gather or monitor crop field data and a PIR (Passive Infrared) sensor was used to improve the device's efficiency by handling frequency transfer and networking activities by broadcasting a small size frame at a distance of 50m. For this communication, the RIOT-OS software is employed, and when the animal is detected, it makes a 120dB sound. PIR sensors have lesser sensitivity and coverage than microwave sensors, and they only operate in LOS (Line of Sight) and will have difficulty in corner locations. [12] utilizes a Raspberry Pi 2 for this project since it is a low-cost single-board computer. PIR sensors are used to detect motion. It has room for development, such as enhanced motion detection employing image processing with night vision cameras.

In conclusion the image-processing based AIDSAF, the raspberry pi 4 model b excels due to specific features such as a faster processor, a 1.5-GHz Broadcom CPU and GPU, larger and faster RAM, the inclusion of USB 3 connections, multiple mini-HDMI connectors (rather than a single HDMI connection), and 4K output capabilities. The YOLOv7 algorithm, which is also scored well in terms of accuracy and computing speed, is the major distinguishing feature of our project. This strategy appears to be very effective in terms of reducing crop damage and saving the lives of trespassing animals by producing customized repellant sounds for individual species and producing notifications to farmers.

CHAPTER 3

METHODOLOGY AND IMPLEMENTATION

3.1 TRANSFER LEARNING

Transfer learning is a machine learning technique that leverages knowledge learned from one task and applies it to a different but related task. It has emerged as a powerful approach in various domains, including computer vision, natural language processing, and speech recognition. By transferring knowledge from a source domain to a target domain, transfer learning enables the efficient utilization of limited labeled data and accelerates the training process, ultimately improving the performance of models.

In traditional machine learning approaches, models are trained from scratch on a specific dataset for a specific task. However, this often requires a large amount of labeled data and significant computational resources. Transfer learning addresses this challenge by allowing models to leverage knowledge acquired from a related task or a large pre-trained dataset. The idea behind transfer learning is that features learned from a source task or dataset can be generalized and applied to a target task, even if the two tasks are not identical.

One of the key benefits of transfer learning is the ability to transfer knowledge about low-level features, such as edges, textures, and basic shapes, which are common across different domains. Instead of starting the learning process from scratch, transfer learning allows models to focus on learning task-specific features and relationships, making the training process more efficient. This is particularly useful when the target dataset is small or lacks diversity, as the model can benefit from the broad knowledge acquired from the source domain.

There are different types of transfer learning approaches, including feature extraction and fine-tuning. In feature extraction, the pre-trained model's convolutional layers are used as a fixed feature extractor, while a new classifier is trained on top of these extracted features for the target task. This approach is beneficial when the dataset is small and similar to the source dataset. By utilizing pre-trained models, which are usually trained on large-scale datasets, models can capture generic and meaningful features that are transferable to the target task.

Fine-tuning, on the other hand, involves unfreezing and updating some of the pre-trained model's layers, allowing them to adapt to the target task's specific characteristics. Fine-tuning is more suitable when the target dataset is larger or significantly different from the source dataset. By updating the model's parameters, it can learn task-specific features while retaining the general knowledge acquired during pre-training. This process can lead to better performance and adaptability to the target task.

Transfer learning has been particularly successful in computer vision tasks, where deep convolutional neural networks (CNNs) have achieved remarkable results. Pre-trained models, such as VGGNet, ResNet, and Inception, trained on large-scale image datasets like ImageNet, have become widely used in transfer learning. These models have learned to recognize a wide range of visual features and patterns, making them valuable resources for various computer vision applications.

In addition to computer vision, transfer learning has shown promising results in natural language processing. Pre-trained language models, such as BERT, GPT, and ELMO, have transformed the field by learning contextual representations from large text corpora. These models capture language semantics and relationships, enabling them to be fine-tuned for specific downstream tasks like sentiment analysis, named entity recognition, and machine translation.

Transfer learning also offers benefits in domains with limited labeled data, as it reduces the need for extensive annotation efforts. By leveraging pre-trained models, even with relatively small labelled datasets, models can achieve competitive performance. This is particularly valuable in real-world scenarios where obtaining labeled data can be time-consuming, expensive, or impractical.

However, transfer learning does come with some considerations. The source and target tasks should be related, as the transferability of knowledge diminishes as the dissimilarity between tasks increases. It is crucial to carefully choose the appropriate pre-trained model and fine-tuning strategy based on the specific characteristics of the target task.

Furthermore, transfer learning has the potential to address domain shift or data distribution discrepancies between the source and target domains. In real-world scenarios, it is common for the available labeled data to come from a different distribution than the target data. By leveraging transfer learning, models can benefit from the knowledge learned in the source domain and adapt it to the target domain, mitigating the effects of domain shift. This is particularly useful in situations like collecting labelled data that precisely matches the target domain is challenging or time-consuming.

Another advantage of transfer learning is its ability to generalize across tasks and domains. By training models on diverse datasets and tasks, they can acquire a broad understanding of underlying patterns and representations. This enables models to generalize well to new tasks or unseen data, making them more robust and adaptable. Transfer learning fosters the development of reusable and transferable knowledge, allowing researchers and practitioners to build upon existing models and accelerate progress in various fields.

In summary, transfer learning is a powerful technique that has revolutionized the field of machine learning, especially in computer vision and natural language processing. By leveraging pre-trained models and knowledge from related tasks, transfer learning enables efficient training, improved performance, and generalization to new tasks and domains. It addresses the challenges posed by limited labeled data, domain shift, and the need for extensive computational resources. As research and development in transfer learning continue to advance, we can expect further breakthroughs and applications in a wide range of fields, leading to more robust and adaptable machine learning systems.

3.2 CONVOLUTION NEURAL NETWORK

Agricultural fields face numerous challenges, including animal intrusions that can lead to crop damage and economic losses for farmers. Traditional methods of animal detection and monitoring are often labor-intensive and time-consuming. However, the emergence of Convolutional Neural Networks (CNNs) has shown great potential in addressing these challenges. This note explores the application of YOLOv7, a popular CNN architecture, for intrusion detection of animals in agricultural fields using a Raspberry Pi 4 Model B, a low-cost and energy-efficient computing platform.

Convolutional Neural Networks (CNNs) are a class of deep learning models specifically designed for analyzing visual data such as images and videos. They excel in tasks like object detection, classification, and localization. CNNs leverage the power of convolutional layers, pooling layers, and fully connected layers to automatically learn and extract relevant features from input data. The architecture of a Convolutional Neural Network (CNN) typically consists of multiple layers that are designed to process visual data efficiently. CNNs have become the go-to choice for computer vision tasks due to their ability to automatically learn and extract features from images. Here is a general overview of the architecture of a CNN:

1. Input Layer: The input layer receives the raw image data, which is usually represented as a matrix of pixel values. The size of the input layer corresponds to the dimensions of the input image.

2. Convolutional Layers: Convolutional layers are the core building blocks of CNNs. They consist of multiple filters or kernels that convolve over the input image to extract local features. Each filter applies a set of weights to a small region of the input image, creating feature maps that highlight different patterns or edges. Convolutional layers help capture hierarchical and spatial relationships within the image.

3. Activation Function: After each convolutional layer, an activation function such as ReLU (Rectified Linear Unit) is applied element-wise to introduce non-linearity into the network. This non-linearity enables the network to model complex relationships in the data.

4. Pooling Layers: Pooling layers are used to downsample the feature maps generated by the convolutional layers, reducing the spatial dimensions while retaining the most important features. Max pooling is a commonly used technique where the maximum value in each pooling region is selected as the representative feature.

5. Fully Connected Layers: Also known as dense layers, fully connected layers are responsible for learning the high-level representations and making predictions based on the extracted features. The output from the convolutional and pooling layers is flattened and connected to the fully

connected layers. Each neuron in these layers is connected to every neuron in the previous layer, allowing for more complex combinations of features.

6. Dropout: Dropout is a regularization technique commonly used in CNNs. It randomly sets a fraction of the output from the previous layer to zero during training, which helps prevent overfitting and improves the network's generalization ability.

7. Output Layer: The output layer provides the final predictions or classifications based on the learned features. The number of neurons in the output layer depends on the specific task. For example, in a classification task, each neuron may represent a different class, and the final prediction is based on the neuron with the highest activation.

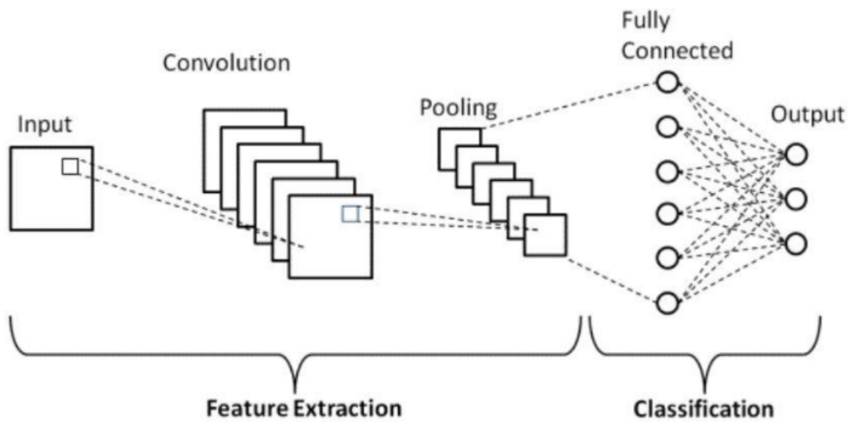

Figure 3.1 Architecture of CNN

The figure 3.1 depicts the architecture of a CNN which can vary depending on the specific problem and network design choices. More advanced architectures, such as VGGNet, ResNet, and Inception, introduce additional layers, skip connections, and parallel pathways to improve performance and address specific challenges. However, the general structure outlined above forms the basis of most CNN architectures.

In the context of intrusion detection systems, CNN refers to the utilization of Convolutional Neural Networks (CNNs) for detecting and classifying intrusions or anomalies in network traffic data. CNNs have shown promise in this domain due to their ability to automatically learn and extract relevant features from input data.

In an intrusion detection system, network traffic data is typically represented as a sequence of packets, each containing various attributes and features. CNNs can be employed to process and analyze this data, leveraging their capabilities in capturing spatial and temporal patterns.

The CNN architecture used in intrusion detection systems typically involves a combination of convolutional layers, pooling layers, and fully connected layers. Convolutional layers perform convolution operations on the input data to extract local features, capturing patterns that may indicate potential intrusions. Pooling layers are used to downsample the feature maps, reducing the spatial dimensions while retaining important information. Fully connected layers process the extracted features and make predictions about the presence of intrusions or anomalies.

The training process of a CNN for intrusion detection involves feeding labeled network traffic data into the network and iteratively adjusting the network's parameters to minimize the detection error. The network learns to recognize and differentiate between normal network traffic and potentially malicious or anomalous patterns.

By using CNNs in intrusion detection systems, it becomes possible to automatically detect and classify various types of intrusions or anomalies, such as denial of service attacks, port scanning, network intrusions, and other suspicious activities. CNNs can learn intricate patterns and relationships in the network traffic data, making them effective at detecting both known and previously unseen intrusions.

Overall, the use of CNNs in intrusion detection systems enhances the ability to detect and respond to potential security threats in real-time, helping to protect computer networks and systems from unauthorized access and malicious activities.

3.3 YOLOV7

YoloV7 is an object detection model that evolved from the YOLO (You Only Look Once) model family. It is a deep neural network-based model that detects objects in real-time video streams or pictures using convolutional neural networks (CNNs). The "V7" in YoloV7 refers to the YOLO algorithm's seventh edition. To identify objects of various sizes and forms, the YoloV7 model employs anchor boxes, which are pre-defined bounding boxes of diverse sizes. YOLO employs solely convolutional layers, resulting in a completely convolutional network. YOLO is made up of 75 convolutional layers, with skip connections and upsampling layers taken into account [1].

The YoloV7 model is trained on a huge dataset of labelled pictures. The model learns to modify the weights of its parameters during training in order to minimize the discrepancy between the predicted objectness score and class probability and the ground-truth labels for the objects in the picture. This is accomplished by the use of a loss function, which penalizes the model for generating inaccurate predictions.

YOLOv7, or You Only Look Once version 7, is a state-of-the-art object detection algorithm that has gained significant popularity and achieved impressive results in various computer vision applications, including intrusion detection systems in agricultural fields. It builds upon the success of its predecessors, YOLOv1, YOLOv2, YOLOv3, and YOLOv4, by introducing architectural improvements and optimization techniques to enhance accuracy and efficiency.

In the context of intrusion detection systems in agricultural fields, YOLOv7 offers several key advantages. Firstly, it enables real-time and accurate detection of animals or intruders, allowing farmers to respond promptly to potential threats and minimize crop damage. YOLOv7 achieves this by dividing an input image into a grid and predicting bounding boxes and class probabilities for objects within each grid cell in a single pass. This eliminates the need for complex region proposal methods and significantly speeds up the detection process.

One of the notable enhancements in YOLOv7 is the introduction of a more powerful backbone network architecture. It utilizes a deep neural network, such as Darknet-53, as the backbone to extract high-level features from the input image. The deeper architecture enables YOLOv7 to capture more intricate and abstract features, leading to improved object detection accuracy, especially for small or partially occluded animals.

Another improvement in YOLOv7 is the implementation of advanced feature fusion techniques. It integrates feature maps from multiple layers of the backbone network using skip connections, allowing the algorithm to leverage both low-level and high-level features for object detection. This feature fusion mechanism enhances the model's ability to detect objects of different scales and appearances, which is crucial in agricultural settings where animals may vary in size and pose. YOLOv7 also introduces techniques to address the problem of small object detection. In agricultural fields, animals like birds or rabbits can be relatively small and challenging to detect accurately. YOLOv7 addresses this issue by employing anchor boxes of different sizes and aspect ratios, enabling the model to better handle objects at different scales. Additionally, the use of focal loss and advanced training strategies, such as mixup and cutmix, helps to alleviate the imbalance between the background and animal classes, further improving the detection performance.

The optimization techniques employed in YOLOv7 contribute to its efficiency and speed. The algorithm incorporates techniques like network pruning, quantization, and model compression to reduce model size and computational requirements. This allows YOLOv7 to be deployed on resource-constrained devices or embedded systems, making it suitable for real-time intrusion detection in agricultural fields without significant hardware constraints.

To train the YOLOv7 model for intrusion detection in agricultural fields, a dataset of annotated images containing instances of animals or potential intruders is required. The dataset needs to be carefully curated and annotated to ensure accurate training and evaluation of the model. Techniques such as data augmentation, which involve artificially generating variations of the original images, can be employed to enrich the dataset and enhance model generalization.

After training, the YoloV7 model may be used to recognize objects by running an image or video stream through it. In real-time, the model predicts the position and class of objects in an image or video stream. Because of its excellent accuracy and rapid processing speed, the YoloV7 model is a popular choice for real-time object identification applications. Because the whole detection pipeline is a single network, detection performance may be optimized end-to-end.

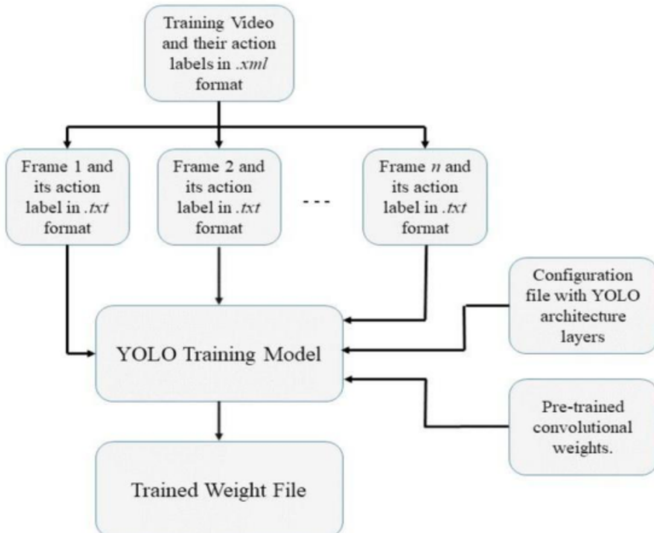

Figure 3.2 YOLOv7 Model-Flowchart

The live captured video feed is analyzed by dividing the whole video into frames that is sort of images for animal detection. Layers and weights are added to the YOLO training model in order to enhance the speed and accuracy of the system in order to get best.pt file as shown in figure 3.2.

In summary, YoloV7 is a deep neural network-based object identification model that detects items of various sizes and shapes using anchor boxes. It is trained on a huge dataset of labelled pictures and can recognise objects in video streams or photographs in real time with great accuracy and speed.

As a result, YOLOv7 requires several times cheaper computing hardware than other deep learning models. It can be trained much faster on small datasets without any pre-trained weights.

In conclusion, YOLOv7 is a powerful and efficient object detection algorithm that can be effectively applied to intrusion detection systems in agricultural fields. Its real-time detection capabilities, high accuracy, and efficient architecture make it a suitable choice for monitoring and protecting crops from animal intrusions. By leveraging the advancements in deep learning and optimization techniques, YOLOv7 offers a robust solution that empowers farmers to detect and respond to potential threats in a timely and effective manner.

3.4 FASTER RCNN

Faster R-CNN (Region-based Convolutional Neural Network) is an object identification model that detects objects in images in two stages. It is a development of the well-known R-CNN model, which was the first to propose the region proposal method for object detection. With its end-to-end training process and shared convolutional features, Faster R-CNN allows for effective transfer learning by leveraging pre-trained models on large-scale datasets. By fine-tuning the network with task-specific data, models can quickly adapt to new domains or tasks with limited labeled data. This transfer learning capability is particularly valuable in practical applications where collecting a large amount of annotated data for each specific task is challenging or time-consuming.

A Region Proposal Network (RPN) and a Fast R-CNN network are the two fundamental components of the Faster R-CNN paradigm. The RPN creates a collection of candidate areas, also known as proposals, that are likely to include objects. After that, the Fast R-CNN network classifies and refines these ideas to provide the final object detection.

The RPN is a fully convolutional network that accepts an image as input and generates a collection of object recommendations with objectness scores. The objectness score shows the likelihood that a proposal will contain an object. To create ideas at multiple locations and sizes in the image, the RPN employs a sliding window technique. The network generates suggestions of various sizes and shapes by using anchor boxes, which are pre-defined bounding boxes of various sizes and aspect ratios.

The Fast R-CNN network takes the RPN suggestions as input and classifies and refines them to provide the final object detection. To extract fixed-size feature maps from each proposal, the Fast R-CNN network employs a RoI (Region of Interest) pooling layer. These feature maps are then sent into a network that classifies and refines the proposals.

During training, the Faster R-CNN model is trained from start to finish with a multi-task loss function. This loss function consists of two parts: a classification loss that penalises the model for wrong class predictions and a regression loss that penalises the model for incorrect bounding box predictions. After training, the Faster R-CNN model may be used to detect objects by sending an image through it. Using the RPN, the model generates a collection of object suggestions and their objectness ratings. After that, the Fast R-CNN network classifies and refines these ideas to provide the final object detection.

One of the notable advantages of Faster R-CNN is its ability to handle multi-class object detection. The algorithm can be extended to detect and classify objects across multiple classes simultaneously. This is crucial in scenarios where there are multiple object categories of interest or when the presence of multiple objects in an image needs to be identified. By leveraging its region proposal and classification capabilities, Faster R-CNN enables comprehensive and accurate multi-class object detection, providing valuable information for various applications.

Faster R-CNN has also inspired subsequent research and advancements in the field of object detection. Building upon the success of Faster R-CNN, researchers have proposed variations and improvements to further enhance its performance. For example, techniques such as Feature Pyramid Networks (FPN) have been introduced to address scale variation challenges and improve object detection accuracy across different object sizes. These advancements continue to push the boundaries of object detection capabilities and further refine the accuracy and efficiency of the algorithm.

Furthermore, Faster R-CNN has found applications beyond traditional object detection. It has been extended to tackle more specific tasks such as instance segmentation and object tracking. Instance segmentation involves both object detection and pixel-level segmentation, which provides a detailed understanding of object boundaries and shapes. Faster R-CNN serves as a strong foundation for such tasks by providing accurate object proposals that can be further refined for pixel-level segmentation. Additionally, the region proposal mechanism of Faster R-CNN can be adapted for object tracking by continuously generating proposals and associating them with objects across consecutive frames, enabling robust and real-time tracking capabilities.

As with any complex algorithm, Faster R-CNN has certain limitations and considerations. The computational requirements of the algorithm can be significant, especially during inference, which may pose challenges for deployment on resource-constrained devices. Efforts have been made to optimize Faster R-CNN for efficiency, such as network pruning and model compression techniques. These optimizations help reduce model size and improve runtime performance, making Faster R-CNN more feasible for real-time applications.

In summary, Faster R-CNN is an object detection model that detects objects in images in two stages. A Region Proposal Network (RPN) creates object suggestions, and a Fast R-CNN network classifies and refines these proposals to provide the final object detection. The model is trained from start to finish with a multi-task loss function and may be used to recognise objects in photos in real time with high accuracy.

In conclusion, Faster R-CNN has made significant contributions to the field of object detection by introducing a region-based approach, unifying the training process, and achieving state-of-the-art performance. Its ability to accurately detect and classify objects in complex scenes, along with its transfer learning capabilities, has transformed various computer vision applications. While it has its limitations, ongoing research and advancements continue to refine and optimize Faster R-CNN, pushing the boundaries of object detection and paving the way for further innovations in the field.

CHAPTER 4
SYSTEM DESIGN AND IMPLEMENTATION

Wildlife incursion is a major problem for farmers in agricultural regions, causing severe crop damage and financial losses. Various technologies have been developed to detect and deter animals from entering agricultural fields in order to address this issue. Traditional methods of animal control, such as fencing and scarecrows, can be ineffective and time-consuming.

This project proposes an image processing-based animal intrusion detection system using Raspberry Pi model in agricultural fields by using deep learning algorithms such as YOLOv7 and Fast RCNN models. By creating virtual boundaries, yolov7 algorithm can identify the presence of animals in agricultural areas with help of raspberry pi 4 model B by analyzing photos collected by cameras installed in the fields and sending SMS notification to farmers or other communication devices. Specific repellent sounds are also produced by speakers in order to scare away the intruding animals.

AIDSAF can help farmers mitigate crop damage and reduce losses by providing real-time alerts indicating the type and location of animals that have entered the field. To generate alerts whenever an animal intrusion is detected using Raspberry Pi, allowing farmers or operators to take necessary actions to protect their crops from further damage. This system provides an efficient and effective solution for preventing crop damage and reducing human-wildlife conflict in agricultural fields.

4.1 ARCHITECTURE

The AIDSAF recognizes with higher accuracy using yolov7 algorithm and produces bee sound that acts as a repellent sound to animals.

4.1.1 BLOCK DIAGRAM OF AIDSAF

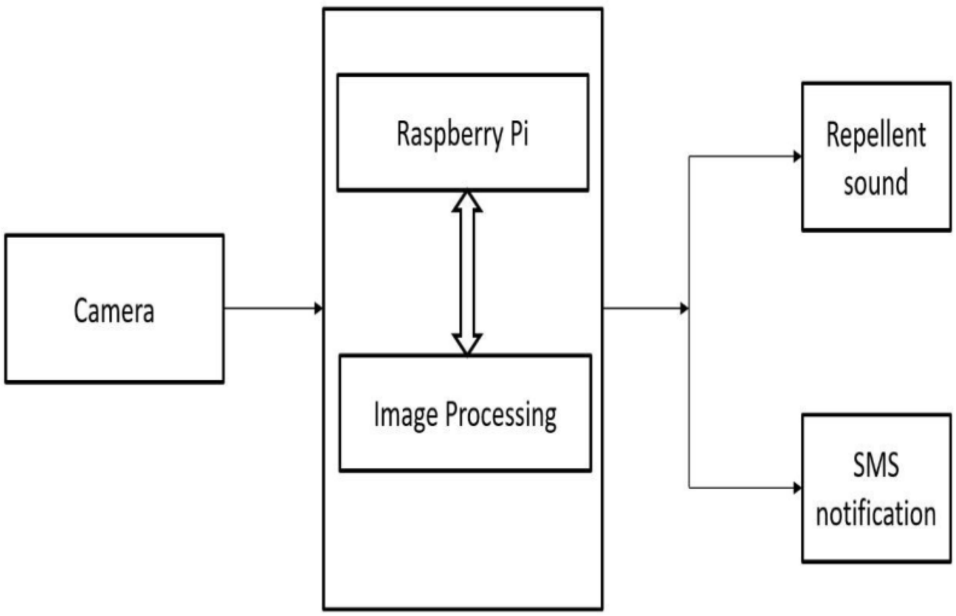

Figure 4.1 AIDSAF Block diagram

The camera which is connected to the raspberry pi is kept in the field to monitor the intrusion, image processing is simultaneously done in order to classify the trained class of animals which is depicted in figure 4.1.

For instance, when an elephant intrudes into the field, The AIDSAF recognizes with higher accuracy using yolov7 algorithm and produces bee sound that acts as a repellent sound to animals. Also generates critical SMS notification to the farmer/ owner of the field. The SMS notification contains important information like, the animal's name, time which will enable the farmer to take further steps to avoid massive crop damage and this method helps to prevent human wildlife conflict.

4.1.2 AIDSAF WORKFLOW

The figure 4.2 shows that the live video is captured by means of webcam. When an animal intrudes into the field where the virtual boundary is created and the raspberry pi4 model B is used to detect the animal intrusion by means of YOLOv7 algorithm. By generating specific repellent sounds for specific animal and simultaneously generating notification to farmers will help to prevent large scale crop damage and human-wildlife conflict.

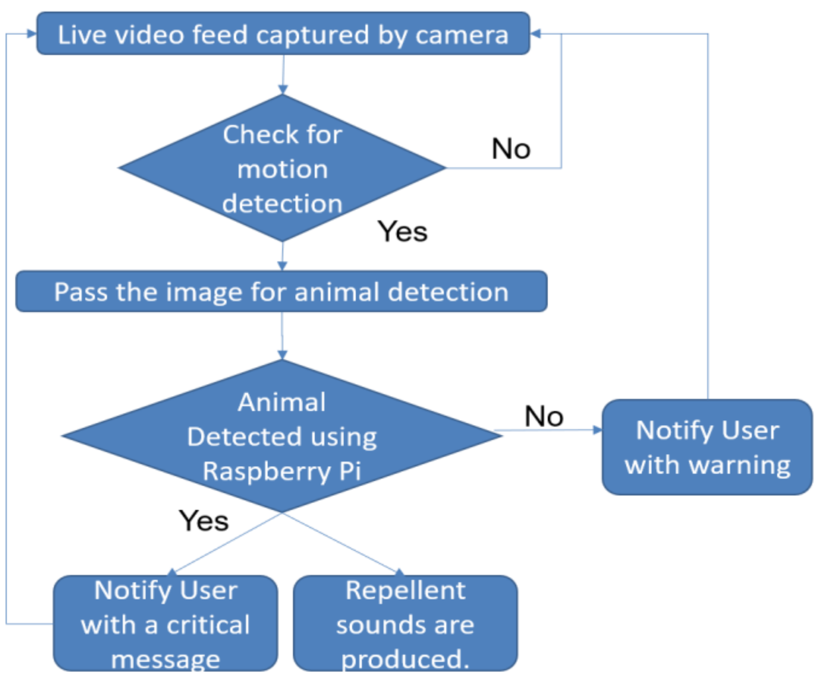

Figure 4.2. Workflow of Proposed model

4.2 COMPARISON BETWEEN YOLOV7 AND FASTER RCNN MODELS

Table 4.1 Comparison between Yolov7 and Faster RCNN

Parameter	Yolov7	Faster RCNN
Architecture	YOLOv7 is a single-stage object detection algorithm that uses a single deep neural network to simultaneously predict bounding boxes and class probabilities. It employs a series of convolutional layers followed by up sampling and down sampling layers to detect objects at multiple scales.	Faster R-CNN is a two-stage object detection algorithm that separates region proposal generation and object classification. It uses a Region Proposal Network (RPN) to generate potential regions of interest, which are then refined and classified by a subsequent network. Faster R-CNN typically incorporates a backbone network, such as VGG Net or Res Net, for feature extraction.
Speed	YOLOv7 is known for its high speed, making it suitable for real-time applications. It achieves real-time object detection by performing a single forward pass through the network, resulting in faster inference times compared to two-stage approaches.	While Faster R-CNN has made improvements in terms of speed compared to its predecessors, it generally has slower inference times compared to YOLO. This is primarily due to its two-stage architecture, which involves multiple passes through the network.
Accuracy	YOLOv7 achieves high accuracy in object detection tasks, with competitive performance on benchmark datasets. It utilizes various techniques, such as feature fusion and advanced loss functions, to improve accuracy and localization precision.	Faster R-CNN is also known for its accuracy in object detection. Its two-stage approach allows for more refined region proposals and precise localization, resulting in high-quality detections.
Handling Small Objects	YOLOv7 struggles to detect small objects accurately. Due to its single-stage nature and the use of larger grid cells for object detection, YOLOv4 may have limitations in detecting small-sized objects.	Faster R-CNN typically performs better in detecting small objects compared to YOLOv4. The two-stage architecture and the use of anchor-based region proposals help in handling small objects effectively.
Training Requirements	YOLOv7 requires a large amount of training data and computational resources for effective training. It benefits from pre-training on large-scale datasets like ImageNet and then fine-tuning on the target dataset.	Faster R-CNN also benefits from pre-training on large-scale datasets, but it generally requires more training time compared to YOLO due to its two-stage nature.

4.3 ALERT GENERATION

When any trained animal enters into the field, the alert is generated by the use of twilio which offers free SMS service. Twilio's free SMS service enables cost-effective communication without requiring additional hardware or subscriptions.

Farmers can receive alerts directly on their mobile devices, allowing them to respond promptly to the intrusion. The SMS notifications can include details such as the type of animal detected, the location within the field, and the time of intrusion, providing valuable information for immediate action. The integration of Twilio's SMS service with the Raspberry Pi-based intrusion detection system enhances the efficiency and effectiveness of monitoring trained animal intrusions in agricultural fields. It enables farmers to proactively address any potential issues, ensuring the safety of both the animals and the crops.

4.4 REPELLENT SOUNDS

Repellent sounds are commonly used in agricultural fields to deter animals and minimize crop damage. These sounds are designed to mimic natural threats or create discomfort for animals, encouraging them to stay away from the protected area. Various types of repellent sounds are employed, including high-frequency noises, predator calls, distress signals, or combinations thereof. These sounds disrupt the animals' feeding or nesting patterns, causing them to seek safer locations. Repellent sound systems, often integrated with technologies like Raspberry Pi, provide a cost-effective and environmentally friendly solution for protecting crops from wildlife intrusions, reducing the need for harmful chemicals or physical barriers.

4.4.1 REPELLENT SOUNDS FOR DOGS

When it comes to deterring dogs, various repellent sounds can be used depending on the situation and objective. Here are a few examples:

- Ultrasonic Sounds: Dogs have sensitive hearing, and ultrasonic sounds can be effective in repelling them. Ultrasonic dog repellent devices emit high-frequency sounds that are not audible to humans but can be uncomfortable or irritating to dogs, causing them to move away from the area.

- Dog Distress Calls: Some repellent devices or applications play recorded sounds of dog distress calls, which can trigger an instinctual response in dogs and discourage them from approaching. These distress calls mimic the sounds dogs make when they are in pain or feeling threatened.

- Predator Sounds: Dogs, like many animals, have an instinctual fear of predators. Playing recorded sounds of predators such as wolves or big cats can create a sense of danger and deter dogs from entering a specific area.

- Human Voice Commands: In some cases, human voice commands or specific words can be used to repel dogs. These commands may be recorded and played through a speaker system, directing the dog to stay away or leave the area.

4.4.2 REPELLENT SOUNDS FOR CATS

When it comes to deterring cats, a variety of repellent sounds can be effective in different situations. Here are a few examples:

- Ultrasonic Sounds: Cats, like many animals, are sensitive to high-frequency sounds. Ultrasonic repellent devices emit frequencies that are unpleasant to cats but generally inaudible to humans. These ultrasonic sounds can deter cats from entering specific areas or discourage them from approaching gardens or crops.

- Hissing Sounds: Cats associate hissing sounds with aggression and danger.

Some repellent devices or applications play recorded hissing sounds, mimicking the warning signals that cats use to communicate their territorial boundaries. This can deter cats from coming near the protected area.

- Loud Noises: Cats are generally sensitive to loud and sudden noises. Clapping hands, banging objects together, or using devices that emit loud noises like air horns can startle cats and make them wary of approaching the area.

4.4.3 REPELLENT SOUNDS FOR SHEEP

Sheep are generally docile and not easily deterred by repellent sounds. However, certain sounds can still be used to create a sense of discomfort or confusion to discourage them from specific areas. Here are a few repellent sound strategies used for sheep:

- Loud Noises: Sudden and loud noises can startle sheep and make them uncomfortable. Devices such as air horns, banging objects together, or clapping hands can create a temporary disturbance that prompts sheep to move away from the source of the sound.

- Distress Calls: Recorded distress calls of sheep or other animals can trigger a sense of danger or alertness among sheep, encouraging them to avoid the area. These distress calls mimic the sounds sheep make when they are in distress, creating a deterrent effect.

- Predator Sounds: Playing recorded sounds of predators that are natural threats to sheep, such as wolves or coyotes, can trigger an instinctual response and cause sheep to be cautious and stay away from the area.

4.4.4 REPELLENT SOUNDS FOR BEAR

When it comes to deterring bears, specific sounds are used to create a sense of danger and discourage their presence. Here are some repellent sound strategies used for bears:

- Loud Noises: Bears are generally wary of loud and sudden noises. Devices like air horns, sirens, or other loud sound-emitting devices can startle bears and create an aversive experience. The goal is to make bears associate the area with a negative stimulus, encouraging them to leave.

- Human Voices: Human voices can be used to deter bears. Shouting, clapping, or using a megaphone to amplify human sounds can signal the presence of humans and create a perception of potential danger for bears. This can prompt them to retreat from the area.

- Bear Alarm Calls: Bear alarm calls are loud and aggressive vocalizations specifically designed to deter bears. These alarm calls can be recorded and played through speakers to simulate the presence of an aggressive bear, triggering a defensive response in the target bear and causing it to leave the area.

4.4.5 REPELLENT SOUNDS FOR ELEPHANTS

When it comes to deterring elephants, specific sounds can be used to discourage them from entering certain areas. Elephants are intelligent and social animals, so repellent sounds should be used with caution and in combination with other deterrent methods. Here are a few examples of repellent sound strategies used for elephants:

- Low-Frequency Rumbles: Elephants use low-frequency rumbles as a form of communication. Playing recorded low-frequency rumbles of dominant elephants or herds can create a perception of competition or threat, causing elephants to be hesitant in approaching the area.

- Loud Noises: Sudden and loud noises can startle elephants and cause them to retreat. Devices such as air horns, firecrackers, or gunshot sounds (without actual gunfire) can create a temporary disturbance that deters elephants.

- Bee Sounds: Elephants are known to be averse to the sound of bees. Playing recordings of buzzing bees or using devices that emit bee-like sounds can deter elephants, as they associate the sound with the potential presence of swarming bees.

4.5 STEPS IN DESIGNING AIDSAF

1. Dataset Preparation:

To train YOLOv7 for animal intrusion detection, a labeled dataset of images containing animals and non-animal objects in agricultural fields is required. This dataset needs to be diverse and representative of different animal species and environmental conditions.

2. Model Training:

The labeled dataset is used to train the YOLOv7 model, where it learns to detect and localize animals in agricultural field images. The training process involves optimizing the model's parameters using techniques like backpropagation and gradient descent to minimize the detection errors.

3. Deployment on Raspberry Pi 4 Model B:

The trained YOLOv7 model can be deployed on the Raspberry Pi 4 Model B, a compact and energy-efficient computing platform. Raspberry Pi provides an ideal solution for real-time animal intrusion detection in agricultural fields due to its low cost, low power consumption, and compact size.

4. Real-time Intrusion Detection:

Once deployed, the Raspberry Pi with the YOLOv7 model can analyze live video feed or images captured by cameras installed in the agricultural fields. The model processes the input frames, identifies and localizes animals, and triggers alerts or actions in case of intrusion. This enables farmers to promptly respond to animal intrusions and mitigate potential crop damage.

4.6 TRAINING THE MODEL

4.6.1 COLLECTION OF DATA

- To create data, animal photographs must first be gathered. We gathered pictures of eight different animal species: dogs, cats, horse, sheep, elephant, bear, cow and bird as shown in table 4.1. We gathered at least 500 pictures of a single animal class to make a training module as shown in figure 4.3. So, in total, we gathered about 4000 pictures. For the picture testing, we gathered unique photographs for each class. Every image contains more than one image and we collected 4000 dataset which contain more than 4000 images. This will aid the training process to achieve higher accuracy.

We gathered at least 500 pictures of a single animal class to make a training module as shown in figure 4.3.

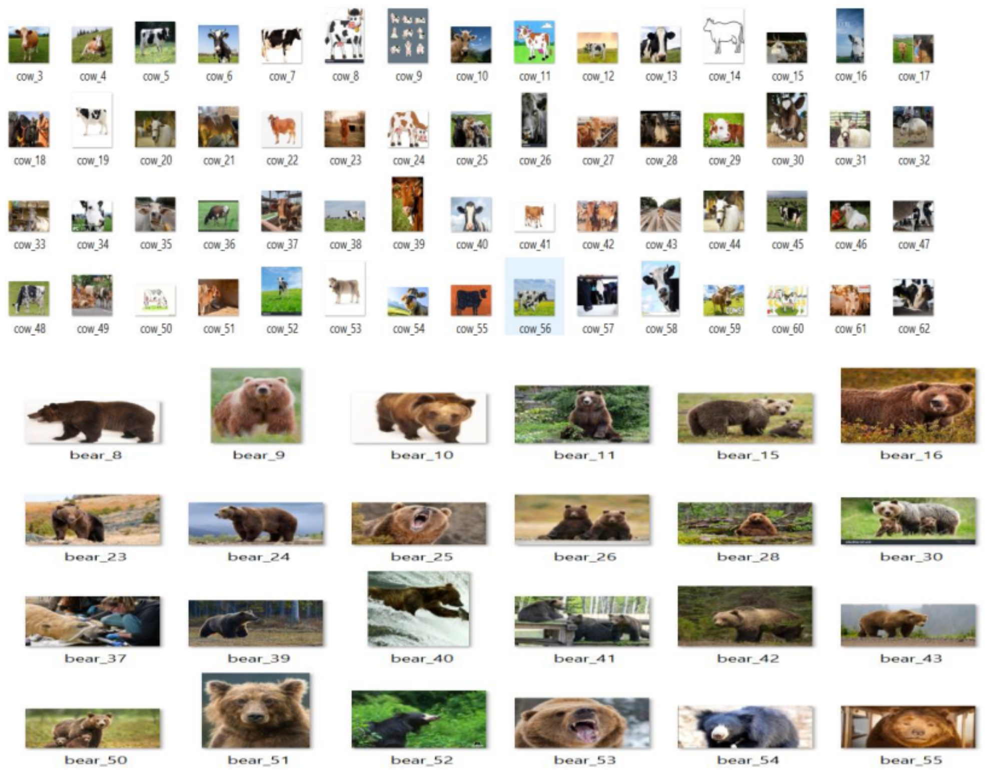

Figure 4.3 Training images

4.6.2 IMAGE LABELING

- Data must be tagged after collection in order to produce a text document that can be used to develop a training module. The images are first accessed, and if it contains the animal classes we need, it is then picked using a bounding box.

- The class of animals defined after the animal is enclosed by a box, as seen in the following Figure:

Figure 4.4 Labels of animals

- To label images we used labelImg in figure 4.4. This tool can detect animal for YOLOv7 and other as well. We can find more than one data in a single image. So, in 4000 images we collected more than 4000 data. In labelImg we have to classified animal from class 1 to class 8. So, we classified animals as:

Table 4.2 Class of animals

CLASS	ANIMALS
Class 1	Cow
Class 2	Bear
Class 3	Elephant
Class 4	Bird
Class 5	Horse
Class 6	Cat
Class 7	Sheep
Class 8	Dog

- Here No. of epochs = 100.
- Training Data: Images: 3000; Labels: 3000
- Where, epoch is a hyperparameter that defines the number times that the learning algorithm will work through the entire training dataset and N is number of classes. To train 8 classes of animals, we have to use 100 epochs.

Table 4.3 Parameters of dataset

BATCH SIZE	**8**
WIDTH	**640**
HEIGHT	**640**
CLASSES	**8**

CHAPTER 5
REQUIREMENT ANALYSIS

5.1 SOFTWARE REQUIREMENTS

5.1.1 PYTHON – 3.9

Python 3.9 is a powerful and popular programming language known for its simplicity and readability. Released in October 2020, it introduced several new features and improvements, making it even more efficient and versatile. With enhanced syntax, performance optimizations, and expanded libraries, Python 3.9 offers developers a seamless coding experience and empowers them to build a wide range of applications, from web development to data analysis and machine learning.

5.1.2 VISUAL STUDIO CODE

Visual Studio Code (VS Code) is a lightweight yet powerful source code editor developed by Microsoft. With its intuitive interface, extensive language support, and a vast ecosystem of extensions, VS Code has gained immense popularity among developers. It offers features like intelligent code completion, debugging capabilities, and Git integration, making it a versatile tool for coding in various languages and frameworks. Its customizable layout and seamless integration with other development tools make Visual Studio Code a go-to choice for efficient and productive software development.

5.1.3 OBS STUDIO

OBS Studio, a popular open-source software for live streaming and video recording, can be installed and utilized on the Raspberry Pi 4 Model B. By running OBS Studio on the Raspberry Pi 4, users can harness the power of this compact computer to capture and stream their screens, webcams, and audio sources. This combination enables content creators, gamers, and enthusiasts to create professional-quality live streams and recordings using the capabilities of the Raspberry Pi 4 Model B.

5.2 HARDWARE REQUIREMENTS

5.2.1 RASPBERRY PI 4 MODEL B

The Raspberry Pi 4 Model B, a small yet powerful single-board computer, has revolutionized the field of embedded systems. Its capabilities, combined with advanced deep learning algorithms such as YOLOv7, enable the development of efficient and cost-effective intrusion detection systems in agriculture. The Raspberry Pi 4 Model B is equipped with a quad-core ARM Cortex-A72 processor, up to 8GB of RAM, and multiple connectivity options. It offers superior computational capabilities, making it suitable for running resource-intensive tasks like deep learning algorithms. The Raspberry Pi 4 Model B supports a variety of operating systems, including Raspberry Pi OS (formerly Raspbian), Ubuntu, and other Linux distributions. The extensive software support and a vast community of developers provide a wealth of resources, tutorials, and projects to explore. The GPIO (General-Purpose Input/Output) pins enable easy integration with sensors, cameras, and actuators.

This processor uses 20% less power and offers 90% greater performance than the previous model. Raspberry Pi 4 model comes in three different variants of 2 GB, 4 GB, and 8 GB LPDDR4 SDRAM.

The other new features of the board are dual-display support up to 4k resolutions via a pair of micro-HDMI ports, hardware video decodes at up to 4Kp60, dual-channel 2.4/5.0GHz wireless LAN, true Gigabit Ethernet, two USB 3.0 ports, Bluetooth 5.0, and PoE capability (via a separate PoE HAT board).

Figure 5.1 Raspberry Pi 4 model B

The above figure 5.1, is connected externally to mouse and keyboard. The power is given externally in order to run the component. The webcam is connected to stream the live video feed. The yolov7 deep learning algorithm is trained and run using raspberry pi in order to make the model portable.

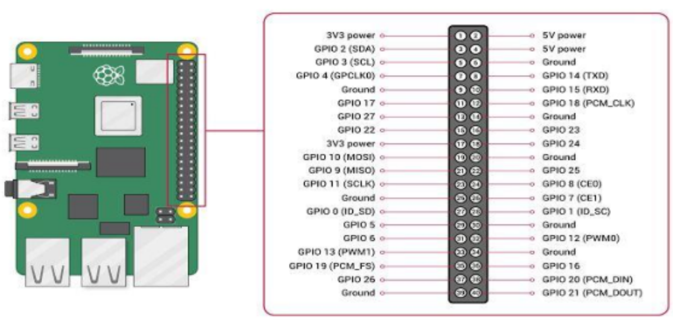

Figure 5.2 Raspberry- pi 4 GPIO output

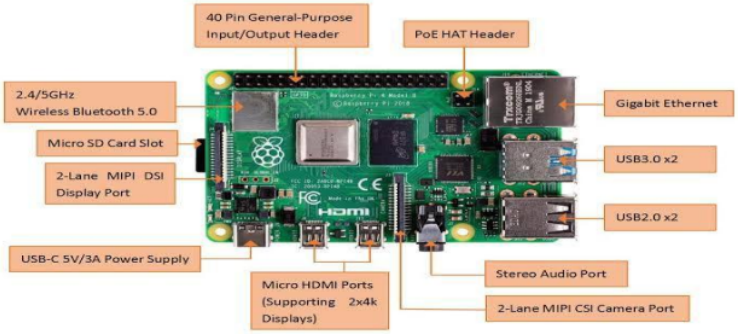

Figure 5.3 Raspberry-pi 4 Board Layout

5.2.1.1 Raspberry-pi 4 Layout

From the above figure 5.3, the raspberry pi 4 model B layout is shown and the components present are:

- **CPU:** It consists of a Broadcom BCM2711 chip which contains a 1.5GHz 64-bit quad-core ARM Cortex-A72 processor (using an ARMv8-architecture core).

- **GPU:** Broadcom VideoCore VI @ 500 MHz was released in 2009. It is capable of BluRay quality video playback, H.265 (4Kp60 decode); H.264 (1080p60 decode, 1080p30 encode); OpenGL ES, 3.0 graphics.

- **RAM:** It comes with 2GB, 4GB, and 8GB (depends on different versions) variants of LPDDR4 SDRAM.

- **USB port:** It consists of two USB 3.0 and two USB 2.0 ports to connect it to an external keyboard, mouse, or other peripheral devices.

- **USB power port:** It consists of a 5.1V, 3A USB type-C power port.

- **HDMI port:** Two micro HDMI ports capable of supporting up to 4k@60HZ resolution.

- **Ethernet Port:** It comes with true Gigabit Ethernet capable of sending *Ethernet* frames at a rate of one *gigabit* per second (1 billion bits per second).

- **Composite Video Output:** Both the audio output socket and the video composite socket reside in a single 4-pole 3.5mm socket.

- **SD card Slot:** A micro-SD card slot is used for booting up the operating system and storage purposes.

From figure 5.4 we can say that the model B consists of a 40-pin GPIO header. Out of these 40 pins, 28 pins are GPIO pins.

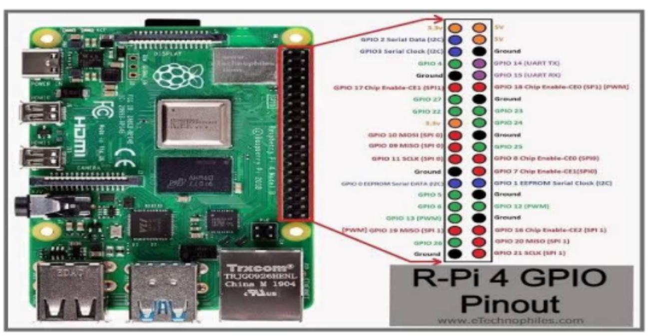

Figure 5.4 Raspberry Pi 4 GPIO Pin Description

5.2.1.2 GPIO Pin Description:

Raspberry pi GPIO stands for General Purpose Input Output pins. These pins are used to connect the Raspberry pi board to external input/output peripheral devices.

Figure 5.5 Raspberry Pi 4 GPIO header

A Standard interface shown in figure 5.5, for connecting a single board computer or microprocessor to other devices through General-Purpose Input/Output (GPIO) pins.

5.2.1.3 Power Pins on Raspberry Pi 4:

The raspberry pi 4 model B board consists of two 5V pins, two 3V3 pins, and 7 ground pins (0V).

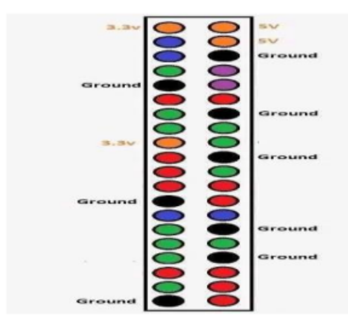

Figure 5.6 Power Pins on Raspberry Pi

The figure 5.6 has the following power pins:

- **5V**: The 5v pin outputs the 5 volts coming from the USB Type-C port.
- **3.3V**: The 3v pin is used to provide a stable 3.3v supply to external components.
- **GND**: The ground pin is commonly referred to as GND.

5.2.2 WEBCAM

A webcam is a video camera which is designed to record or stream to a computer or computer network. They are primarily used in video telephony, live streaming and social media, and security. Webcams can be built-in computer hardware or peripheral devices, and are commonly connected to a device using USB or wireless protocols.

Figure 5.7 Webcam

The webcam in figure 5.7 is externally connected to raspberry pi in order to stream the live video. High quality, long-range, night vision cameras can be installed in case of real time application. Cameras with night vision are used to maximize a video surveillance system's effectiveness in low light conditions. The fundamental feature that unites all such cameras is the presence of IR illumination, without which it is impossible even to imagine video surveillance at night.

A good camera with night vision should have several relevant characteristics:

- Powerful IR illumination, preferably adaptive;
- Ability to switch from color mode to black and white;
- High light sensitivity of the sensor;
- ICR filter;
- Weatherproof housing.

The backlight angle should ideally coincide with the angle of view of the camera lens. Otherwise, the image can get a bright spot in the middle of the frame and dark areas at the edges.

Its power determines the range of the IR illumination, and the greater this parameter, the more power will be required to power it. For example, to provide a distance exceeding 10 meters, the backlight diodes must have a total power of 5-10 W, while the current consumption can increase to 1 ampere. Due to the increased energy consumption, the LEDs of IR illumination rather heat up during operation. Therefore, when located in the cameras with night vision bodies, cooling radiators will be required.

5.2.2.1 Long Range Webcam

A Long-range security camera refers to any security camera that can focus at least 75 feet away from their mounting point and still recognize a person.

5.2.3 SPEAKERS

The use of speakers connected to a Raspberry Pi for producing repellent sounds in agricultural fields offers an innovative solution for deterring pests and wildlife from damaging crops. By leveraging the Raspberry Pi's capabilities, such as its GPIO interface and audio output, a system can be created to emit specific sound frequencies that repel pests and animals. It offers automation, customization, and scalability, allowing farmers to effectively protect their crops while minimizing the use of harmful chemicals or physical barriers.

CHAPTER 6

RESULTS AND ANALYSIS

Using OpenCV we detect if there is any movement in live video feed captured by camera. The video feed is divided into frames to detect any intrusion. The AIDSAF performs at the rate of 30fps using raspberry pi for analyzing and detecting any animal intrusion in agricultural field.

6.1 YOLOV7 RESULT

The individual accuracy of each class of animal in YOLOv7 is represented below:

Figure 6.1 Yolov7 accuracy

6.2 FASTER RCNN RESULT

The detection of each class of animal in Faster RCNN is represented below:

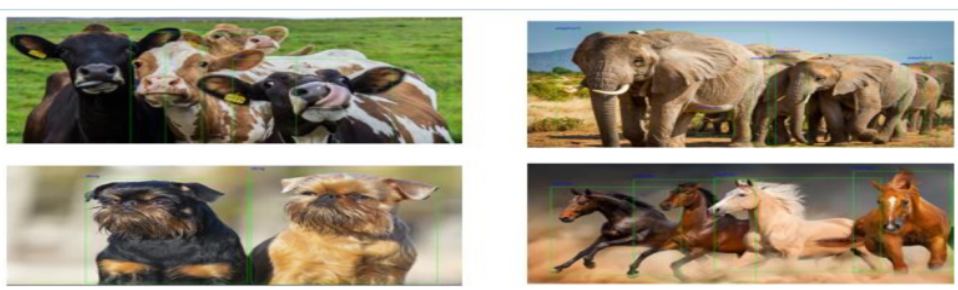

Figure 6.2 Faster RCNN accuracy

From the below table we can conclude that YOLOv7 model is highly efficient in terms of accuracy as compared to Faster RCNN model. When generalizing from natural pictures to other domains such as artwork, it outperforms other detection approaches such as DPM and R-CNN [7].

6.3 COMPARING ACCURACY FOR 8 CLASSES

Table 6.1 Accuracy comparison

CLASS	YOLOv7	Faster RCNN
Cow	96%	81%
Bear	95%	88%
Elephant	99%	92%
Bird	92%	97%
Horse	96%	90%
Cat	100%	82%
Sheep	92%	94%
Dog	97%	83%

6.4 AIDSAF SIMULATION RESULT

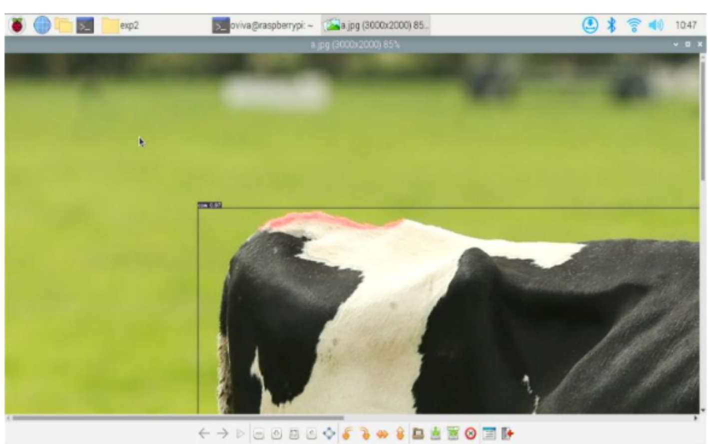

Figure 6.3 Animal Detection

The above figure 6.3 shows the output of the animal detection in raspberry pi 4 model B when it enters the specified boundary. We have trained 8 classes and when the cow image is passed for testing, the yolov7 code in raspberry bi 4 model B detects the animal with a higher accuracy.

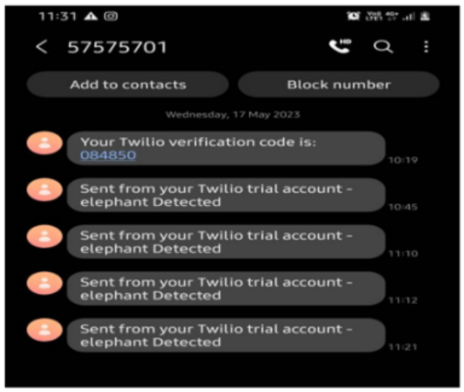

Figure 6.4 Alerts generated

Figure 6.4 shows that alert is generated to farmers via SMS notification by means of twilio which is a free service. Alerts are generated to user when a desired animal intrudes into the specified boundary. For instance, in the above fig 10. We can note that the elephant has intruded at that specific time period.

Figure 6.5. Intrusion detection

The above figure 6.5 is the output of the animal intrusion detection in raspberry pi 4 model B. When an elephant is intruded inside the specified agricultural boundary, the alerts are generated via SMS and simultaneously the repellent sound is played in order to scare away the animal. For example, in this case honey bee sound is played as elephants are irritated by this particular noise. The main aim to drive the animal away from the agricultural field is achieved. Therefore, preventing human wildlife conflict and crop mitigation.

6.5 ADVANTAGES

- **Early Detection:** The system can detect intruding animals in real-time, allowing farmers to take immediate action to prevent damage to their crops. Early detection can also prevent harm to both the animals and the farmers.
- **Accuracy:** Image processing algorithms using deep learning can accurately identify animals in images, even in low-light or adverse weather conditions, which can improve the accuracy of the detection system.
- **Cost-Effective:** The use of cameras and image processing software can be more cost-effective compared to traditional methods, such as hiring security personnel or using physical barriers.
- **Non-Invasive**: The system is non-invasive and does not require any physical interaction with the animals. It can detect the presence of animals without disturbing their natural behavior.
- **Scalability:** The system can be scaled up or down depending on the size of the agricultural field. The number of cameras and the processing power required can be adjusted accordingly.

- **Automated Alerts:** The system can automatically generate alerts when animals are detected, allowing farmers to respond quickly and efficiently.

6.6 APPLICATION

The application of intrusion detection using YOLOv7 on Raspberry Pi 4 Model B can extend beyond agricultural fields and find utility in various other fields. Here are some examples of how this solution can be applied in different domains:

- Wildlife Reserves and National Parks:

  In wildlife reserves and national parks, the detection of animal intrusions is crucial for ensuring the safety of wildlife and preventing human-wildlife conflicts. By deploying the YOLOv7-based system, park rangers and conservationists can monitor protected areas more effectively, detect potential poaching activities, and respond swiftly to any intrusions that may endanger the wildlife.

- Urban Surveillance and Security:

  In urban environments, the intrusion detection system can be utilized for surveillance and security purposes. It can be deployed in public spaces, parking lots, or residential areas to detect unauthorized entry, trespassing, or suspicious activities. The real-time detection and alerting capabilities enable law enforcement agencies or security personnel to respond promptly to potential security threats.

- Industrial Facilities and Critical Infrastructure:

Critical infrastructure, such as power plants, factories, or transportation hubs, often require high-level security measures. The YOLOv7-based intrusion detection system can be integrated into existing surveillance systems to detect unauthorized access or intrusions into restricted areas. It enhances the overall security posture and helps prevent potential sabotage, theft, or unauthorized actions within these critical facilities.

- Perimeter Security in Residential Areas:

The solution can be deployed in residential areas to enhance perimeter security. It can be used to monitor the boundaries of private properties, detect intrusions into fenced areas, or identify potential security breaches in gated communities. Homeowners can receive real-time alerts on their mobile devices, enabling them to take immediate action or notify authorities if any suspicious activity is detected.

- Animal Conservation and Research:

The YOLOv7-based system can support animal conservation efforts by monitoring and tracking endangered species in their natural habitats. Conservationists and researchers can deploy the system to detect and identify specific animals, record their movements, and gather valuable data for population studies, habitat preservation, and wildlife behavior research.

- Traffic Monitoring and Safety:

The solution can be utilized for traffic monitoring and safety applications. By installing cameras equipped with the YOLOv7-based system at key locations, it becomes possible to detect traffic violations, such as red light running, illegal parking, or pedestrian crossings. This aids in improving road safety, enforcing traffic regulations, and optimizing traffic management systems.

- Retail and Shopper Analytics:

  In the retail industry, the intrusion detection system can be employed for shopper analytics and store security. By tracking customer movements within a store, retailers can gather data on customer behavior, traffic flow patterns, and popular areas. This information can be utilized for store layout optimization, product placement, and enhancing overall customer experience. Additionally, the system can help detect shoplifting or suspicious activities, reducing retail losses due to theft.

These examples illustrate the versatility and wide-ranging applications of the intrusion detection system based on YOLOv7 and Raspberry Pi 4 Model B. Its ability to detect and monitor objects in real-time opens up opportunities for improved security, safety, conservation, and data-driven decision-making in various fields. It helps in preventing crop damage and animal-deaths due to electrocution from illegal power fence. The use of the intrusion detection system helps the government to maintain border security and prevent illegal crossings, which can pose a threat to national security. The use of the intrusion detection system helps the company to maintain high-security measures and protect sensitive information and assets. The system saves time and money that would have been spent on hiring additional security personnel to monitor entry points.

CHAPTER 7
CONCLUSION AND FUTURE SCOPE

The image-processing based AIDSAF implemented using YOLOv7 algorithm utilizes a webcam to capture live video feed of the agricultural fields, detects and analyzes the intrusion using Raspberry Pi 4 model B and DL model. If an intrusion is detected, the system produces repellent sounds with help of speakers and also sends an alert to farmers. The YOLOv7 model is highly preferred in terms of accuracy and speed. By this method the animal lives are in less threatening position and also the main aim to protect the field from damage is achieved. The data set of classes can be expanded and each image in the class can be maximized for even better accuracy. Our future works include the usage of drones which will give a bird's eye view for enhanced security and monitoring. More powerful and night vision cameras can be used in our future development.

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IMAGE PROCESSING BASED ANIMAL INTRUSION DETECTION SYSTEM IN AGRICULTURAL FIELD USING DEEP LEARNING

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Abstract: *Agriculture is one of the most important industries in any economy since it plays a big role in the food supply chain. Agricultural fields, on the other hand, confront a number of issues, including animal encroachment, which can cause severe crop damage and loss. Traditional animal control tactics, such as electrical fences, physical barriers, and scarecrows, can be inefficient, time-consuming and a serious threat to animal lives. The animals either become entangled in the fence's wire mesh or were electrocuted by the electric lines. To overcome these problems we propose a unique method that involves image processing-based animal incursion detection system in agricultural fields using Raspberry Pi and deep learning technique, mainly the YOLOv7. This technology captures live video feeds of agricultural fields using a camera and analyses them using deep learning algorithm to detect any animal invasions. If an intrusion is detected, the system emits specific repellent sounds for specific animal via speakers in order to scare them away and alerts the farmers by sending SMS. This method provides an efficient and practical alternative for crop damage prevention and human-wildlife conflict reduction in agricultural settings.*

Keywords: *Animal Intrusion Detection System in Agricultural Fields - AIDSAF*

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