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# Animal Intrusion Detection Model Based On Temporal Convolutional Network.

Jaishri C
Electronics and Communication Engineering
Bannari Amman Institute of Technology Sathyamangalam
jaishri.ec20@bitsathy.ac.in

Abinesh R
Electronics and Communication Engineering
Bannari Amman Institute of Technology Sathyamangalam
abineshr.ec20@bitsathy.ac.in

Naveen V
Electronics and Communication Engineering
Bannari Amman Institute of Technology Sathyamangalam
naveen.ec20@bitsathy.ac.in

***Abstract*—This project proposes an innovative wildlife management system utilizing computer vision and machine learning for precise animal detection and ultrasound-based repelling. Integrated with edge computing, the system offers real-time responsiveness to mitigate crop raiding while minimizing environmental impact and addressing financial constraints. The solution aims to safeguard crops and public infrastructure by effectively deterring various wildlife species. Additionally, a user-friendly dashboard enables incident monitoring and alerts. This adaptable solution extends beyond agriculture to diverse settings, providing a balanced approach to wildlife protection.**

***Keywords*— Species-specific Repellent, Wildlife Management, Computer Vision, Temporal Convolutional Network (TCN), Interactive Dashboard.***

## I. Introduction

Human-wildlife conflicts arising from habitat encroachment and urbanization present significant challenges in agricultural areas and urban environments. Traditional wildlife management methods are proving insufficient and environmentally damaging, necessitating innovative solutions leveraging Artificial Intelligence (AI) and edge computing technologies. Our project aims to address these challenges by developing a smart wildlife management system integrating AI and edge computing to protect crops and public infrastructures like parks and gardens from wildlife intrusions. Despite advancements in agricultural technology, farmers and custodians of public infrastructures continue to grapple with wildlife intrusion threats, posing risks to crop productivity, food security, and public safety. Conventional pest control methods may not be viable for organic farming or maintaining ecological balance in public spaces, necessitating a sophisticated and humane approach. This project seeks to promote coexistence between humans and wildlife while safeguarding agricultural productivity and urban green spaces by combining cutting-edge technology with sustainable design principles.

## II. Ease of Use

The proposed wildlife management system is designed with ease of use as a priority, ensuring accessibility and practicality for users. The system integrates user-friendly interfaces and intuitive controls, allowing for seamless operation by farmers, park administrators, and other stakeholders. Additionally, the system's dashboard provides real-time monitoring and incident alerts, enabling quick response and intervention when wildlife intrusions occur. By prioritizing ease of use, the system enhances efficiency and effectiveness in mitigating human-wildlife conflicts while minimizing the need for extensive training or technical expertise.

## III. Objective

The objective of this project is to develop an Integrated Wildlife Management System utilizing machine learning techniques to detect and deter animal intrusion effectively. Through the implementation of a robust temporal convolutional network (TCN)-based computer vision model, the system aims to accurately identify and categorize invasive species in real-time. Upon detection, the system will utilize targeted ultrasonic emission technology within the Animal Repelling Module to emit species-specific ultrasound frequencies, discouraging wildlife from raiding crops and entering public spaces like parks and gardens. Leveraging edge computing technology ensures rapid response times, enabling timely activation of deterrent measures upon animal entry. Furthermore, the system prioritizes environmental sustainability by employing non-lethal repellent methods, thus minimizing ecological impact and promoting coexistence between agriculture and biodiversity. Additionally, the project seeks to address financial constraints associated with traditional wildlife management techniques by developing a cost-effective and reliable solution, enhancing accessibility and scalability for users and agricultural communities alike.

## IV. Scope of the Project:

The product has been iterated over a period of time. Some of the innovative ways in which this product stands out are:

- Usage of a combination of Camera Vision to detect intrusion of any animal entering the farm, parks or highways.
- Usage of the electrical signal to trigger an alarm that repels the detected animal away.
- Solar-powered set-up

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● Since animals tend to get acquainted to the recurring sounds and lights in their surroundings, ordinary alarming systems will work in the beginning but its effectiveness will decrease sharply with time. To overcome this shortcoming, AniRep uses permutations and combinations of Vision and sound patterns that changes every time an intrusion is detected. This delays habituation in animals. As our system is deployed in rural areas, where energy efficiency is essential, we evaluated some Hardware and Software architectural alternatives for the design and implementation of the AI embedded Edge computing components to be added to our system.

## V. PROPOSED Methodology

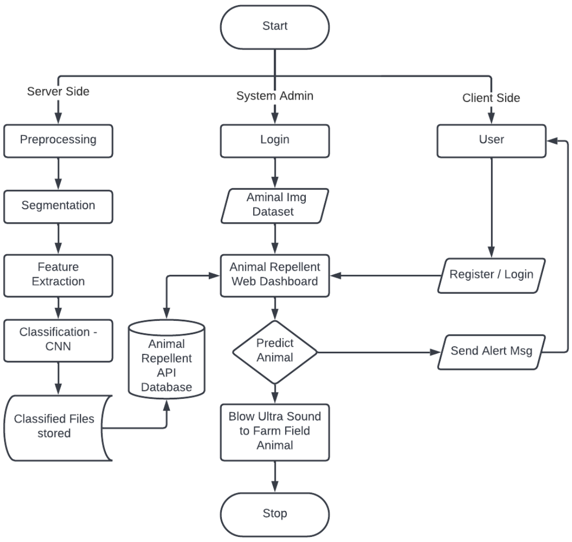


***Figure 5.1:*** *Workflow Diagram*

### Wildlife Defense Web App

Python is used in the design and development of this Wildlife Defence Web App. MySQL is used for database administration, Flask serves as the web framework, and Bootstrap provides a user interface that is both visually appealing and responsive. Because of the web application's safe user authentication mechanism, administrators and users may access various features according to their responsibilities. The system's user-friendly interface enables administrators to create and train WildNet models. The training process is made easier by image classification and labeling features, and effective real-time detection is ensured by deploying taught models to edge devices. Using an easy- to-use interface, administrators may set up ultrasonic repellents for each species.

This feature improves the defensive mechanism of the system by tailoring and deploying ultrasonic emissions according to predictions made by the WildNet model. A geographical overview of edge device locations and active repellent zones is provided via a map interface.
Administrators and users may remotely watch animal activity across fields thanks to this capability. Users may monitor real-time field data from anywhere in the world over the internet thanks to the facilitation of remote access. A strong alarm system included into the web app alerts users in real time when it detects wildlife trespass. For quick reaction times, manual controls are integrated, including buzzer activation.

### End User Interface

#### a. Admin Interface

**Login:** Using a special login page, administrators may safely access the system and guarantee permitted access. A secure login procedure is ensured by a number of measures, including username-password combinations.

**Submit Datasets:** To train the WildNet model, administrators may quickly and easily submit a variety of datasets containing tagged photos of animals. Enhancing species recognition, the system supports several picture formats and guarantees appropriate labeling for precise model learning.

**Creating the WildNet model:** Admins start and oversee the training of WildNet models in a separate part. Epochs, learning rates, and model topologies are examples of customizable parameters that enable exact customization and optimization during training.

**Deploy Model:** After the WildNet model has been successfully trained, administrators deploy it to edge devices. In order to guarantee compatibility with target devices and effective integration into the wildlife protection system, the deployment procedure is meticulously evaluated.

**Integrate Ultrasound:** Using an intuitive interface, administrators link certain wildlife species' ultrasound emissions. This feature promotes targeted and compassionate wildlife deterrent by enabling the customization and setup of ultrasonic repellents in accordance with each trained model.

**Update the Model:** In response to new datasets or changing requirements, administrators may continue to update and retrain the WildNet model. The mechanism enables smooth updates, guaranteeing that the model adjusts to evolving animal behaviors and conditions without any interference

#### b. User Interface

**Register:** Users may use the system to start interacting with it by registering and entering basic information about themselves, including name, contact information, and farm location. Verification procedures are part of the registration process, which improves system security and data accuracy.

**Login:** Using secure credentials, authenticated users access their accounts, guaranteeing a private and secure login experience customized to each user's unique profile.

**Real-Time Monitoring:** Users have access to a dashboard that shows live video feeds from their farms in real-time. With the use of the dashboard's useful insights, which include deployed WildNet model status, ultrasonic

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activation information, and intrusion alarms, users may have instant visibility into their farming operations.

**View Animal infiltration Report:** Users have access to thorough reports on animal infiltration occurrences that provide information on species identification, intrusion trends, and the efficacy of countermeasures used. The reports facilitate well-informed decision-making for efficient management of wildlife.

**Manual Controls:** Users use the interface's manual controls, such as buzzer activation or other deterrent measures, when an emergency calls for quick response. This feature improves the system's proactive defensive capabilities by enabling users to react quickly to any attacks.

**WildNet Model: Build and Train**

To create and train the WildNet model, this module integrates CNN-based classification, pre-processing, sophisticated image processing methods, and dataset gathering. The Wildlife Defence Web App Firmware's integration of the trained model improves the system's capacity to identify and classify wildlife, offering a strong defensive mechanism for agricultural lands.

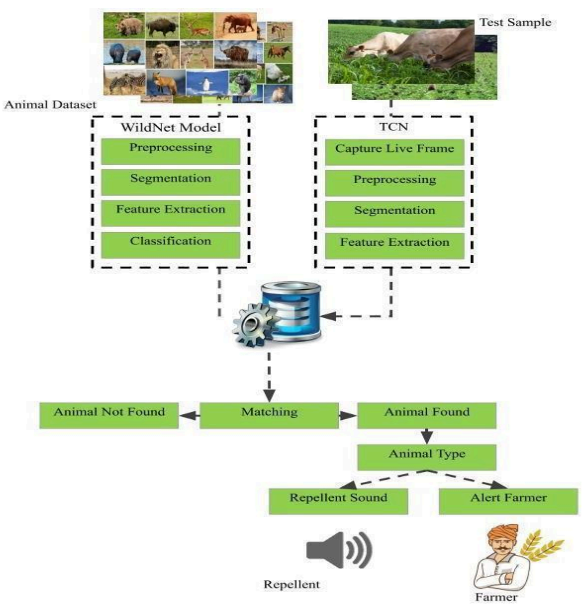


*Figure 5.2 Wildnet Model*

**Import Dataset:**

The administrator imports the gathered dataset into the Wildlife Defence Web App Firmware. The smooth incorporation of the dataset into the training process is ensured by this phase.

**Visualize the Dataset:**

Administrators can see the dataset to learn more about the traits and variety of the photos. Making judgments on pre-processing is aided by this phase in comprehending the distribution of data.

**Pre-processing:**

The actions done to prepare photos before they are utilized for model training and inference are known as animal image pre-processing. The actions to be performed are:

- RGB to grayscale picture conversion
- Image resizing: Original dimensions (360, 480, 3) (Height, breadth, and number of RGB channels)
- enlarged to (220, 220, 3)
- Denoise (remove noise)
- To get rid of extraneous noise, smooth our photograph. We use Gaussian blur for this.

Image binarization is the process of turning a grayscale image to black and white. This reduces the image's information from 256 shades of gray to only two, or black and white, creating a binary image.

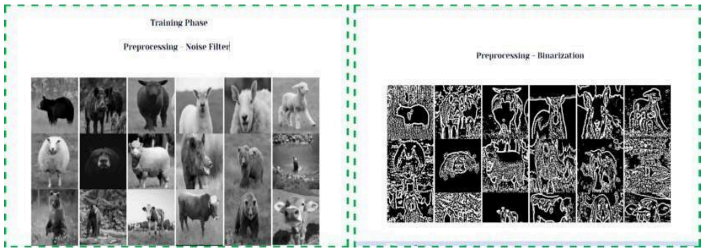


*Figure 5.3 Binarization of Gray Scale Images*

**Animal Segmentation:**

Consequently, the Region Proposal Network (RPN) in this module creates ROIs by using anchors with varying sizes and aspect ratios to slide windows over the feature map. A method for segmenting and detecting animals using enhanced RPN. ROIs are generated using RPN, and ROI Align accurately maintains the precise spatial placements.
They are in charge of supplying a predetermined collection of bounding boxes in various sizes and ratios that will be utilized as a point of reference when first estimating the positions of objects for the RPN.

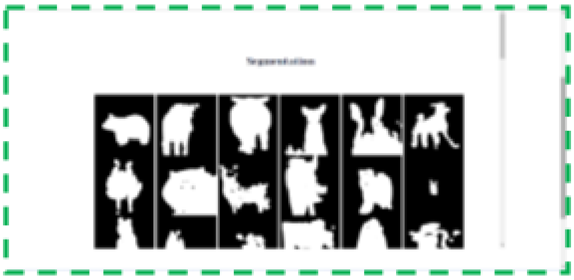

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*Figure 5.4 Segmentation*

**Feature Extraction:**

Statistical, shape, color, and texture features are the forms in which the image's valuable information or attributes are retrieved throughout the feature extraction process. Feature extraction is the process of converting the input picture into features. Techniques for feature extraction are used to extract features. Texture, boundary, spatial, edge, transform, color, and shape characteristics are used to extract features.
Boundary and region-based features are two categories of shape-based features. Boundary segment-based boundary features are also known as contour-based features. The characteristics that are based on boundaries include those that are geometric (such as diameter, main and minor axes, perimeter, eccentricity, and curvature), Fourier, and statistical (such as mean, variance, standard deviation, skew, energy, and entropy). Texture characteristics as GLCM are based on regions.

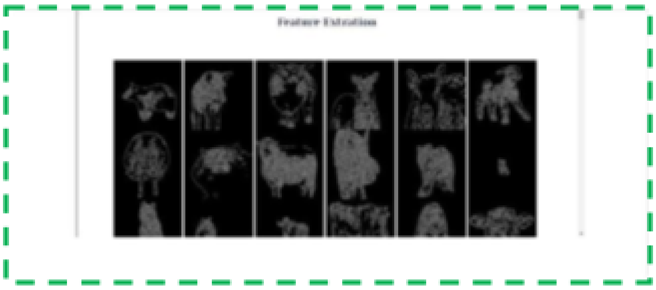

*Figure 5.5 Feature Extraction*

**Animal Classification:**

During the categorization phase, CNN algorithms were used to automatically identify and reject inappropriate animal photos. This will guarantee appropriate instruction and, thus, optimal output.

By adding up the convolved grid of a vector-valued input to the kernel with a bank of filters to a certain layer, the CNN generates feature maps. Next, the convolved feature maps' activations are calculated using a non-linear rectified linear unit (ReLU). Local response normalization (LRN) is used to normalize the new feature map that was acquired from the ReLU. A spatial pooling approach is used to further compute the output from the normalization (maximum or average pooling). Next, certain unneeded weights are initialized to zero using the dropout regularization approach, this process often occurs inside fully linked layers before to the classification layer. Lastly, within the fully linked layer, picture labels are classified using the SoftMax activation function.

**Build and Train the WildNet**

The CNN architecture is the foundation upon which the WildNet concept is built. For the best training results, parameters including batch sizes, learning rates, and epochs are set. During the training phase, the model's weights are adjusted to reduce loss and increase accuracy.

**Deploy the WildNet model**

The Wildlife Defense Web App Firmware uses the taught WildNet model when training is accomplished. This guarantees that the model is prepared for application in agricultural areas for real-time animal detection and classification.

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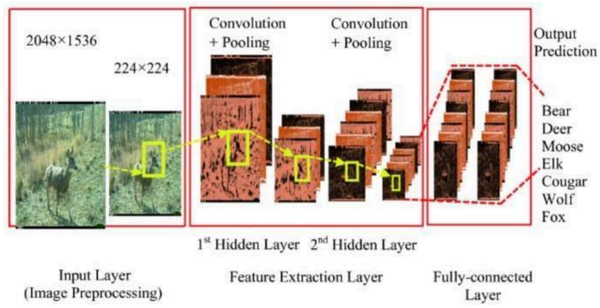


**Figure 5.6. Animal Classification**

By adding up the convolved grid of a vector-valued input to the kernel with a bank of filters to a certain layer, the CNN generates feature maps. Next, the convolved feature maps' activations are calculated using a non-linear rectified linear unit (ReLU). Local response normalization (LRN) is used to normalize the new feature map that was acquired from the ReLU. A spatial pooling approach is used to further compute the output from the normalization (maximum or average pooling). Next, certain unneeded weights are initialized to zero using the dropout regularization approach, this process often occurs inside fully linked layers before to the classification layer. Lastly, within the fully linked layer, picture labels are classified using the SoftMax activation function.

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**Deploy the WildNet model**

The Wildlife Defense Web App Firmware uses the taught WildNet model when training is accomplished. This guarantees that the model is prepared for application in agricultural areas for real-time animal detection and classification.

**Animal Identification**

The image of the animal is sent to the animal detection module once it has been captured by the Camera. This module identifies the areas of a picture that are probably inhabited by people. The animal picture is sent into the feature extraction module once the animal has been detected using the Region Proposal Network (RPN) in order to identify the critical features that will be utilized for classification. The module creates a very brief feature vector that suffices to depict the picture of the animal.

**Ultrasound Sound Integration**

- The system keeps track of an ultrasonic sound library with sounds associated with various animal species. This library is a collection of different ultrasonic emitters, each designed to ward off a certain kind of animals. Using the settings panel, administrators may upload, update, and maintain the ultrasound sound database.
- Through the setup panel, administrators have fine- grained control over the ultrasonic emissions' frequency and intensity. By adjusting these factors, the deterrent impact may be maximized and customized according to the unique sensitivities of various animal species.

**Animal Intrusion Predictor**

Whether in recorded movies, live video streams, or input photos, the Animal Intrusion Predictor module with Temporal Convolutional Networks (TCN) is engineered to detect and forecast the presence of animals. The neural network design known as TCN is frequently employed in sequence modeling, which makes it a good fit for jobs that need temporal relationships, including video analysis.

**Input Modalities**

**Image Input:** Users can provide single images as input to the system for animal detection.

**Live Video Input:** The module can process live video streams in real-time, identifying animals as they appear.

**Video Input:** Users can analyze pre-recorded videos, allowing retrospective analysis of animal intrusion.

**Temporal Convolutional Networks (TCN)**

Managing temporal dependencies in visual data requires the use of TCN. It works well for jobs involving videos because of its exceptional ability to recognize patterns and characteristics over consecutive frames.

**Animal Recognition:** The module has been taught to identify and detect different kinds of animals. To do this, characteristics and patterns from the incoming data must be learned in order to provide precise predictions.

**Prediction Output:** The system provides predictions about the existence of animals together with details like the kind of animal found and a confidence level.

**Animal Identification:** In addition to determining if animals are there, the system also determines which kind of animal is present in the input data. Common animals like dogs, cats, birds, etc., may fall within this category.

**Confidence Scores:** The module assigns a confidence score to each prediction, signifying the system's degree of assurance about the animal it has found. In the process of making decisions, this score may be helpful.

**Real-time Visualization:** The Wildlife Defence Web App or monitoring interface dynamically displays the forecasts in real-time. Users may actively monitor and react to animal incursions as they happen thanks to this functionality.

**Ultrasound Emission**

The module uses the Animal Intrusion Predictor's outputs to predict possible wildlife invasions using predictive logic. This preventive measure makes sure that ultrasonic emissions happen before, or just after, the actual breach.

**Activation Trigger in Real Time**

When the Animal Intrusion Predictor detects an animal intrusion, real-time ultrasound emissions are set off. The module ensures quick and targeted deterrent by smoothly integrating with prediction results.

**Controls for Emergency Override**

Administrators has the power to manually activate ultrasonic emissions during emergency overrides. In situations where instant deterrent is needed, this manual control guarantees a prompt reaction.

**Monitoring and Visualizing**

In addition to allowing users to remotely observe their crops, the device detects animals in the field in real time. It is possible to specify the animal's kind and number. Using a Wi-Fi connection, the animal recognition module will routinely communicate the data over the cloud. The cloud configuration will consist of a private cloud instance running on a computer. The pooled data will be used to examine wild animal behaviors and trends. If there are any mistakes, the user can see them, fix them, and get better outcomes.

**Alerts or Notification**

The Animal Intrusion Predictor and Ultrasound Emission modules are easily connected with the Alerts or Notifications module. This integration makes sure that when the system detects important events such as wildlife invasions, ultrasound emissions, or other occurrences, alarms will be set off. Several channels are used to transmit notifications in order to make them accessible. In-app alerts inside the Wildlife Defence Web App, SMS notifications, email alerts, and other user-configured communication channels may be examples of this. Images of animals, timestamps, and comprehensive details about the triggering event are all included in the notifications. This information helps users be aware of their surroundings and gives them context so they can comprehend the purpose and timing of each warning.

## VI. Proposed Work Module

This project presents an integrated system aimed at addressing wildlife-related challenges in agriculture and other public infrastructures by combining advanced AI technologies with targeted ultrasound emissions and user alert mechanisms. The system utilizes Temporal Convolutional Network (TCN) and WildNet for accurate detection and recognition of animal species, coupled with species-specific ultrasound emissions for repelling identified animals. Additionally, the system incorporates an alert system to notify users via SMS when potential threats are detected.

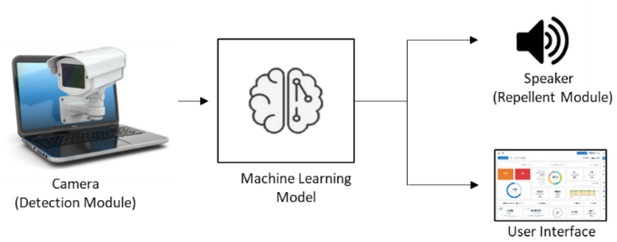


***Figure 6.1*** *Overall Flow Diagram*

### *a) AI Computer Vision Module*

The TCN and WildNet form the core of the computer vision module, offering real-time video analysis for accurate detection and recognition of animal species. This component processes high-resolution imagery captured by cameras deployed in any areas, improving the system's ability to identify and classify wildlife accurately.

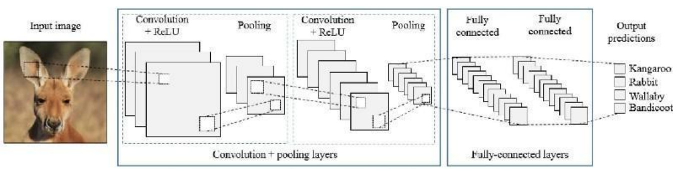


Figure 6.2 Convolutional Neural Network

### *b) Convolutional Layer*

The central component of a convolutional network, the convolutional layer, handles the majority of the computational labor-intensive tasks. Extraction of features from the picture input data is the main function of the convolution layer. By employing tiny squares of the input image to learn image attributes, convolution maintains the spatial link between pixels. A group of learnable neurons is utilized to create a convoluted input image. The resulting image is then transformed into a feature map, also known as an activation map, which is then used as input data for the subsequent convolutional layer.

*Pooling Layer:* Each activation map retains the most crucial information even after the dimensionality is decreased by the pooling layer. A collection of non-overlapping rectangles is created from the supplied photos. A non-linear procedure, such as average or maximum, is used to down sample each region. This layer is typically positioned between convolutional layers and offers improved generalization, quicker convergence, robustness to translation, and distortion resistance.

*ReLU Layer:* Units using the rectifier are included in the non-linear operation known as ReLU. It reconstitutes all negative values in the feature map by zero and is an element-wise operation, meaning it is applied per pixel. The rectifier is defined as f(x)= max (0, x) in the literature for neural networks. This helps us understand how the ReLU works if we assume that there is a neuron input supplied as x.

*Fully Connected Layer:* The phrase "fully connected layer" (FCL) describes a situation in which all filters in one layer are connected to all filters in the next. High-level elements of the input image are embodied in the output of the convolutional, pooling, and ReLU layers. Using these features to categorize the input image into different classes based on the training dataset is the aim of using the FCL. The final pooling layer, or FCL, is thought of as providing the features to a classifier that employs the SoftMax activation function. The Fully Connected Layer's output probabilities add up to 1. By employing the SoftMax as the activation function, this is guaranteed. A vector containing any number of real-valued scores can be squashed by the SoftMax function to create a vector of values that add up to one between zero and one.

### *c) Ultrasound Emission Module*

In general, animals are significantly more sensitive to sound than people are. They are able to perceive noises at frequencies that are lower than those of the human ear. For example, humans can hear between 64 and 23 kHz, but goats, sheep, domestic pigs, dogs, and cats can hear between 78 and 37 kHz, 10 Hz and 30 kHz, 42 Hz and 40.5 kHz, 67 Hz and 45 kHz, and 45 Hz and 64 kHz. When ultrasonic waves are produced in the critical detectable range, they startle animals and force them to move away from the source of the sound. However, even in cases where the ultrasound's frequency range exceeds that of the human ear, there is no harm done to the human ear by these scans. Compared to animal eardrums, human have a far lower particular resonance frequency and are incapable of ultrasonic vibration. Furthermore, this kind of remedy is non-lethal, doesn't pollute the ecosystem, and doesn't alter the scenery. When the computer vision module detects a threat, the ultrasonic emission is set off with the intention of driving away the observed species. Effectiveness against targeted species is ensured by careful design, which also minimizes influence on non-targeted entities.

### *d) User Alert System*

When possible, dangers are detected, the alarm system notifies the user. Pre-registered users receive up-to-date information about recognized species and potential hazards through warning signals. The users are better equipped to react quickly to wildlife incursions because to this instantaneous and customized communication.

### e) *User Interface*

Users can interact with the system on an intuitive platform thanks to the user interface. Through this interface, users can set up parameters, view real-time data, and get warnings. It gives users control and insights by offering options for changing species recognition models, modifying sensitivity levels, and maintaining contact details for SMS warnings.

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