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Animal Guard: CNN-Driven System for Real-Time Animal Detection in Human Habitats

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Abstract: This paper presents the development of a real-time animal detection system, designed to identify wild animals using a live webcam feed and Convolutional Neural Networks (CNNs). The system aims to improve wildlife monitoring by providing real-time detection of animals and alerting users through both auditory and message notifications. By leveraging advanced image recognition techniques, the system can accurately detect and classify various animal species, making it a valuable tool for wildlife conservation and human safety. The platform integrates seamlessly with a user-friendly website built using the Django framework, where users can observe the detection process in real time. The website displays which animals have been detected, allowing users to monitor wildlife activity remotely. Upon detecting an animal, the system immediately triggers an alarm and sends a notification to designated users, ensuring prompt awareness of potential wildlife presence. This dual-alert mechanism enhances safety by enabling quick responses to animal sightings, thereby helping to manage human-wildlife conflicts. The core of the detection process is powered by Convolutional Neural Networks, which have been trained to recognize different animal species from the live video feed. These networks offer a robust solution for real-time image processing and classification, delivering high accuracy in identifying wildlife.

Keywords: Real time animal detection, Wild life Conservation, Convolutional Neural Network (CNN), Django framework

1.INTRODUCTION

Animal intrusion into farmlands, especially by elephants, presents a significant challenge to farmers, threatening the health of crops and causing substantial financial losses. This issue is not limited to elephants alone; other animals, such as deer, wild boars, and rodents, also pose considerable threats. These animals can ravage crops, impact local economies, and contribute to larger problems, including food shortages and rising food prices. Traditional methods of human surveillance have proven ineffective, requiring constant vigilance that is both labor-intensive and inefficient. Given these challenges, it is essential to explore alternative, more effective solutions for protecting farmland from animal incursions.The economic impact of animal intrusion on farmland is profound. Crops are often destroyed in the process, resulting in significant financial losses for farmers, particularly smallholder farmers who rely on these crops for their livelihoods. The loss of crops not only affects the farmer but also disrupts the supply chain, leading to food shortages in local markets. This can further escalate the price of food, impacting the wider community, especially in rural areas where food security is already precarious.In addition to financial concerns, animal intrusion can lead to the loss of biodiversity and ecological imbalance. As animals enter farmlands, they may destroy not only crops but also surrounding vegetation, leading to soil degradation and reduced fertility. This makes it harder for farmers to recover in the long term, as the land becomes less productive over time. Moreover, the presence of these animals can introduce diseases to livestock, adding yet another layer of concern for farmers who already face numerous challenges.

Traditional surveillance methods, such as manually guarding the fields, have proven to be ineffective. These methods require a significant amount of manpower and are often unsustainable, especially in

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regions with large areas of farmland. Farmers are typically unable to monitor their fields 24/7, and even if they could, the risk of human-wildlife conflict, particularly with large and dangerous animals like elephants, poses a significant risk to the safety of farmers. These methods are also reactive rather than proactive, meaning that the damage is often done by the time any action is taken. As a result, there is an urgent need for more efficient and effective solutions that can provide real-time monitoring and proactive prevention of animal intrusion. One of the most promising solutions to this problem lies in the integration of technology into agricultural practices. Advanced technologies such as sensors, drones, and even trained animals are revolutionizing the way farmers can protect their crops from animal incursions. By leveraging these tools, farmers can not only monitor their fields more effectively but also take proactive steps to prevent damage before it occurs. Sensors, for example, can be strategically placed throughout farmlands to detect the presence of animals. These sensors work by detecting movement or specific sounds, such as the footsteps of large animals like elephants. Once an animal is detected, the sensor can send an alert to the farmer or trigger automated systems, such as lights or sounds, designed to scare the animals away. This provides farmers with a real-time, 24/7 monitoring system that is far more efficient than traditional methods. Additionally, some sensors can be linked to automated deterrent systems that activate upon detection of animals, such as releasing specific sounds that deter wildlife from entering the farmland. Drones equipped with advanced imaging technologies offer another layer of protection. These drones can survey large areas of farmland quickly and efficiently, providing farmers with an aerial view of their fields. They can be used to spot animals from a distance, allowing farmers to take action before the animals reach the crops. Drones can be especially useful in areas with dense vegetation or difficult terrain, where it is challenging to maintain constant surveillance on foot. Furthermore, drones can be equipped with thermal imaging cameras to detect animals at night, when they are most likely to enter farmlands undetected.

In addition to sensors and drones, trained animals, particularly dogs, play a crucial role in detecting intruders. Dogs possess heightened olfactory senses that make them excellent at detecting the presence of animals from a distance. They can be trained to alert farmers when an animal is approaching, providing another layer of security for the farmland. Unlike electronic systems, dogs can also provide a physical deterrent to some animals, further reducing the likelihood of intrusion.By combining these technological tools, farmers can create a comprehensive system for protecting their crops from animal intrusion. These tools not only provide real-time monitoring but also allow for swift and proactive responses to potential threats. This, in turn, helps to mitigate the financial impact of animal incursions, safeguard farmers' livelihoods, and ensure food security for the wider community. The integration of technology into traditional farming practices represents a significant step forward in creating a more sustainable and resilient agricultural system. By using sensors, drones, and trained animals to monitor and protect farmland, farmers can reduce their reliance on labor-intensive and inefficient methods of surveillance. This not only improves the overall efficiency of farming operations but also reduces the risk of human-wildlife conflict, which can be dangerous for both the farmers and the animals involved. The article is organised as follows. The works related to recent advancements of wild life tracking included in next session. The proposed works along with methodology has been discussed in session 3. The results and discussions are included in session 4. The prescribed work has been concluded in session 5 with its future scope.

2. REVIEW OF LITERATURE

Protecting crops from wildlife incursions poses significant challenges, particularly as agricultural lands expand into areas traditionally inhabited by animals, resulting in increased conflicts. Farmers in India contend with threats not only from pests and natural disasters but also from wildlife, which leads to diminished crop yields. Conventional protective measures often fall short due to the impracticality of constant monitoring. Thus, a careful balance between human safety and wildlife protection is essential[1]. This project addresses these issues by employing machine learning techniques, specifically neural networks in computer vision, to detect animals entering agricultural fields. Through the use of cameras that periodically monitor these areas, a deep learning model can identify intrusions and employ sound cues to gently redirect animals away from crops. By leveraging various libraries and convolutional neural networks, the initiative aims to mitigate crop damage while ensuring the safety and welfare of both human and animal populations. Recently, advancements in edge computing have greatly improved the capabilities of real-time applications by localizing processing and storage near the devices themselves. This development results in lower latency, improved response times, and secure data transfers. The current study centers on Smart Agriculture, focusing specifically on safeguarding crops from threats posed by ungulates through the use of virtual fences that integrate computer vision with ultrasound technology. The primary device in this setup generates ultrasound waves[2] to deter these animals, incorporating features that enable it to detect and recognize various species and adjust the ultrasonic signals as needed. The solution also addresses the energy and connectivity limitations prevalent in rural areas by utilizing IoT platforms, effectively balancing performance, cost, and energy efficiency. Implementing edge computing hardware such as Raspberry Pi and NVIDIA Jetson Nano with real-time object detection models like YOLO demonstrates the practicality of this system, ensuring efficient animal detection on low-power devices without sacrificing accuracy. Furthermore, the research includes a thorough cost and performance evaluation of each hardware and software platform, offering valuable insights for farmers and agronomists in their management strategies.

Protecting crops from wildlife incursions is essential for both food security and the financial viability of farmers. Our proposed model combines IoT technology with machine learning to tackle this issue. A Raspberry Pi serves as the core of the machine learning system, integrated with components such as an ESP8266 module, Pi Camera, buzzer, and LED lights. Utilizing technologies like Region-based Convolutional Neural Networks and Single Shot Detection (SSD), the system can accurately detect and classify animals. Experimental results indicate that SSD outperforms Region-based Convolutional Neural Networks in terms of both speed and accuracy. The integration of the Twilio API allows for real-time communication with farmers, enabling them to respond quickly to threats of crop damage[3]. Surveillance plays a critical role in various contexts, particularly in agriculture, where it serves to prevent unauthorized access and protect crops from animal-related damage. Farmers encounter considerable risks from wildlife, including boars, birds, and rodents, which can lead to significant economic losses and reduced harvests, sometimes forcing them to abandon their fields. Our system[4] addresses these challenges by providing effective farmland surveillance and employing edge computing technology to deter wild animals. This strategy minimizes latency, enhances response times, and ensures secure data transmission. The Smart Agriculture application utilizes computer vision and ultrasound emission to establish virtual fences, generating species-specific ultrasound to protect crops humanely. The deployment of animal detection systems on energy-efficient edge computing devices proves the feasibility of the solution without compromising precision or real-time performance. This article includes an extensive cost and performance analysis of each platform, offering practical guidance and best practices to aid farmers and agronomists in making informed decisions and optimizing their management processes[5].

In farming communities, wildlife such as elephants, cows, goats, and birds inflict considerable damage to crops, resulting in substantial financial losses for farmers. The feasibility of continuous surveillance or erecting physical barriers is often limited. To address this concern, we propose a smart crop protection and alerting system centered around a microcontroller. This system employs motion and sound sensors to detect animal movements or specific frequencies associated with approaching wildlife. Once an animal is detected, the sensors activate the microcontroller, which sends an SMS notification to the farmer, facilitating prompt action to safeguard their crops. This solution ensures that farmers can respond effectively to ongoing wildlife threats.

This survey is designed to examine the interactions between wild animals and humans in various environments. Utilizing camera traps, drones, and sensors, it gathers data on the presence, behavior, and habitat utilization of animals in diverse settings, including forests and agricultural areas. By analyzing this information alongside social and economic data from local communities, the survey aims to pinpoint conflict areas, such as instances of crop damage or livestock predation. This thorough approach will inform the development of strategies to alleviate these conflicts, fostering harmonious coexistence and supporting the conservation of wildlife populations. The insights gained from this survey will be invaluable for policymakers, conservationists, and local communities as they collaborate to devise sustainable solutions for human-wildlife interactions.

3. PUBLIC SURVEY

This survey is focused on exploring the interactions between wild animals and humans in diverse settings. It employs tools such as camera traps, drones, and sensors to gather information on animal activity, behaviour, and habitat use in areas like forests and farms. By combining this data with social and economic insights from local populations, the survey aims to highlight conflict zones, such as those where crop damage or livestock attacks occur. The goal is to use this comprehensive analysis to design effective strategies that reduce conflict, encourage peaceful coexistence, and preserve wildlife populations. The results will provide valuable guidance for policymakers, conservationists, and local communities as they work together to create sustainable approaches to managing human-wildlife interactions. Important queries and the responses that included in the survey are given below

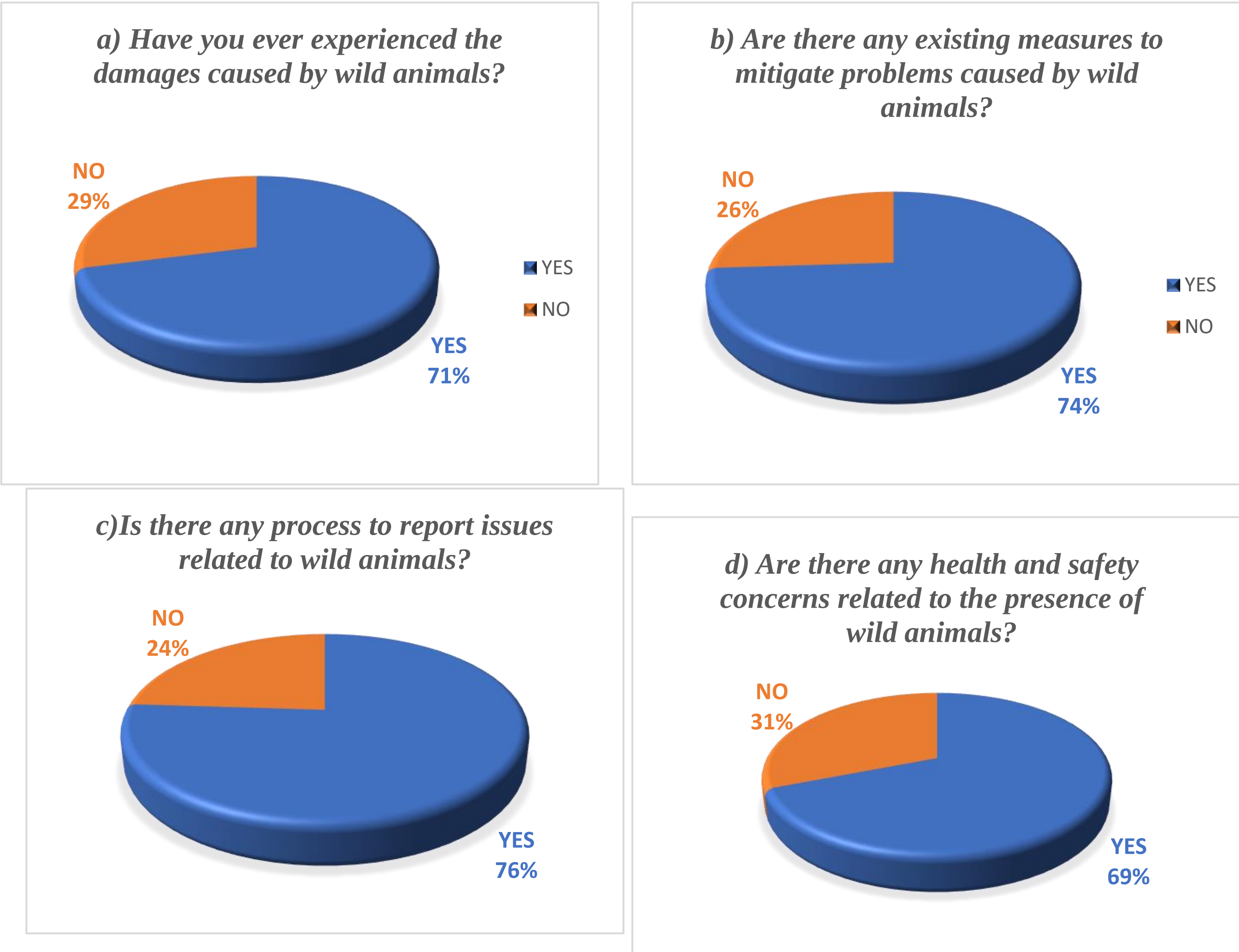


Fig.1. Survey Queries and responses

A recent survey has revealed that residents in the area frequently encounter wild animals but lack adequate measures to safeguard their farms or receive timely alerts about wildlife in the vicinity. This emphasizes the need for a thorough understanding of human-wildlife interactions.To meet this need, a detailed survey is being conducted, focusing on wildlife detection through the use of advanced technologies such as camera traps, drones, and sensors. These tools help gather data on wildlife presence, behavior, and distribution across different habitats. By integrating this information with social and economic data from local communities, the survey aims to pinpoint conflict areas and propose strategies to reduce these tensions, fostering coexistence and conserving wildlife populations. The results will serve as an important resource for policymakers, conservationists, and local communities, aiding them in developing sustainable approaches to managing human-wildlife interactions.

4.METHODOLOGY

4.1 Proposed System Hardware Description

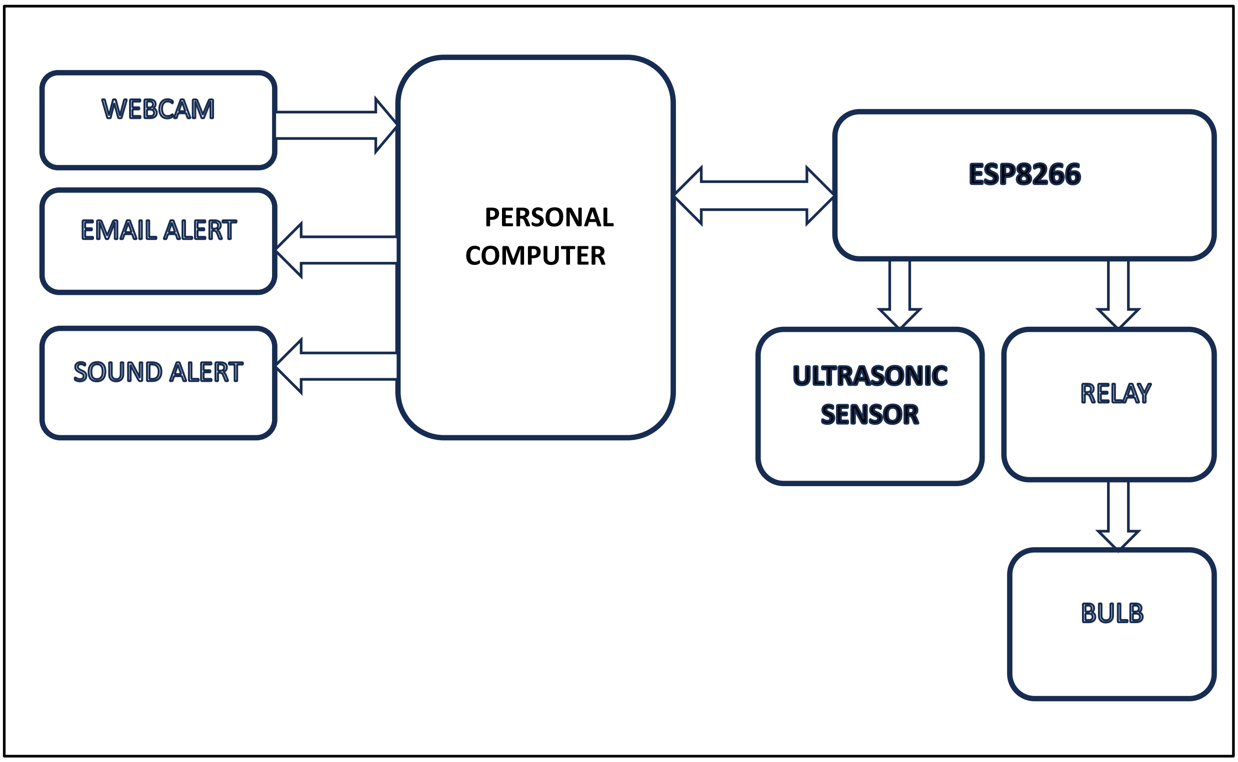


Fig.2 Block Diagram of Proposed System

This animal detection system integrates a PC, webcam, and NodeMCU for real-time wildlife monitoring. The PC functions as the system's core, analyzing the video stream from the webcam using computer vision to detect animals. Once an animal is detected, the PC communicates with the NodeMCU, a microcontroller, which then triggers notifications, such as sending emails or sounding alarms. The NodeMCU can also control additional devices, such as a buzzer, to execute further actions based on the detection. The webcam continuously captures footage, which serves as input for the PC's analysis. This setup can be configured to send email alerts, display animal type and distance information, and visually highlight detected animals within the images. NodeMCU is an open-source platform for developing IoT (Internet of Things) products, powered by the ESP8266 Wi-Fi module from Espressif Systems, offering built-in Wi-Fi connectivity, making it ideal for internet-connected devices. It supports Lua scripting and the Arduino IDE, allowing developers to code in C++ and access numerous Arduino libraries. The hardware includes GPIO pins for connecting sensors and actuators, a USB-to-Serial converter for programming, and debugging, along with a voltage regulator to ensure a stable 3.3V power supply. With 4MB of flash memory for storage, NodeMCU is versatile for various IoT applications, from home automation to remote monitoring. Getting started involves installing the necessary software, connecting the NodeMCU to a computer, writing and uploading code, and refining the design based on testing results. With its ease of use, affordability, and active community, NodeMCU is a solid choice for IoT developers at all levels.

The HC-SR04 ultrasonic sensor is a popular and cost-effective solution for distance measurement, commonly used in robotics and automation. It works by emitting ultrasonic sound waves from its transmitter and measuring the time it takes for the waves to reflect off objects and return to its receiver. The sensor calculates distance by timing the echo, leveraging the known speed of sound. Operating at 4.5V to 5.5V, it can detect objects within a 2 cm to 400 cm range, with an accuracy of about 3 mm. It has four pins: VCC for power, GND for ground, TRIG to initiate the pulse, and ECHO to send the signal back. This sensor is widely employed in applications such as obstacle avoidance, level detection, and proximity sensing due to its simplicity and reliability.Infrared (IR) LEDs used in animal deterrent systems emit light within the infrared spectrum, invisible to humans but detectable by many animals. These LEDs are often incorporated into motion-activated devices to deter animals from specific areas. Operating wavelengths generally range between 700 and 1000 nanometers, with higher wavelengths, such as 850nm or 940nm, being more effective for repellent purposes. The LED's beam angle impacts the coverage area, and wider angles are preferable for larger spaces. Durability and weather resistance are essential for outdoor usage, along with power efficiency, especially for battery-operated systems. Reviewing specifications like power consumption, operating voltage, and temperature is important for ensuring performance in different conditions. A buzzer is used as a sound-producing electro-acoustic device, commonly used for alarms or alerts. Buzzers come in two primary types: active and passive. Active buzzers have an internal oscillator, requiring only a direct current to function, while passive buzzers need an external signal to produce sound. Key specifications include voltage, current, frequency, and sound output level. Voltage ratings typically range from 3V to 12V, and sound output is measured in decibels (dB). Choosing the appropriate buzzer involves matching these specifications to the intended application to ensure optimal performance for alert or signaling purposes.A webcam is used as a digital camera that captures live images or video, typically connecting to a computer via USB or wirelessly. It includes a lens, an image sensor, and processing software, enabling real-time communication through video conferencing, live streaming, and remote monitoring. Many webcams also feature built-in microphones and adjustable resolution settings, making them useful for a range of applications, from remote communication to security surveillance.Django is a powerful, high-level Python web framework designed for rapid development and scalability. It follows the Model-View-Controller (MVC) pattern, where models define the data, views handle the user interface, and controllers manage the application logic. Django includes built-in features such as an ORM (Object-Relational Mapping), authentication, URL routing, and a templating engine to simplify the development process. Emphasizing the DRY (Don't Repeat Yourself) principle, it promotes clean, maintainable code with reusable components. With extensive documentation, a strong community, and support for numerous plugins, Django is a popular choice for building secure, scalable web applications.

TensorFlow, an open-source machine learning framework developed by Google Brain, is highly regarded for its versatility and robustness. It allows developers and researchers to build complex neural networks efficiently using computational graphs for data flow. TensorFlow's capabilities span a wide range of applications, including natural language processing, computer vision, and reinforcement learning. Its ease of use, supported by rich documentation and a large community, makes it suitable for both beginners and experts in deep learning and AI.OpenCV (Open Source Computer Vision Library) is a popular library for computer vision tasks. It enables machines to interpret and process visual data from images and videos. OpenCV is widely used for tasks like face and object recognition, image processing, and machine learning. This tutorial covers various topics, such as image reading, Canny Edge Detection, contour analysis, template matching, and blob detection using Python. OpenCV helps machines understand digital images, making it a key tool for developing applications in fields like robotics, surveillance, and augmented reality.

A Convolutional Neural Network (CNN) is a specialized deep learning algorithm designed to handle structured grid data like images. Inspired by the human visual system, CNNs excel at identifying patterns and features in visual data. The architecture of a CNN consists of several key layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply filters (kernels) to the input images, performing convolutions to extract features such as edges, textures, and shapes. Each filter generates a feature map, highlighting specific features in various regions of the image.Next, pooling layers—commonly max pooling—are used to down-sample the feature maps, reducing their dimensionality. This step decreases computational complexity and reduces the risk of overfitting, making the model more robust to small variations in the input. Following the convolution and pooling layers, fully connected layers use the flattened feature maps to perform high-level reasoning and classification. Activation functions like ReLU (Rectified Linear Unit) introduce non-linearity, allowing the network to learn more complex representations. Additionally, techniques like dropout can be applied during training to prevent overfitting by randomly deactivating some neurons in the fully connected layers.CNNs have transformed the field of computer vision and are widely used in various applications, such as image and video recognition, medical image analysis, autonomous vehicles, and facial recognition. Their ability to automatically learn spatial hierarchies of features makes them powerful tools for visual data processing.

In this project, one of the most crucial steps involves collecting image data of animals, including images from CCTV footage—either real-time or recorded. After collecting the data, pre-processing is essential since not all images are immediately useful. Pre-processing steps include renaming, resizing, and labeling the images to prepare them for training the deep learning model.Next, we must import the necessary libraries, which contain functions and code to assist in object detection and image processing. Libraries like TensorFlow, OpenCV, and Keras will play key roles in optimizing our deep learning model for handling real-time images or videos.Once we gather datasets for the animals, it's important to connect a camera to the deep learning model. The camera will act as the computer's eye, capturing real-world objects for the model to detect. Using the camera, we can monitor various environments, and the detected animal data can serve as evidence if needed.

4.2 Logic Flow of Proposed System

The logic flow for the system begins with capturing images or video frames using a webcam connected to a computer. These visuals are then processed through an animal detection algorithm running on the PC, which scans the frames to identify the presence of any animals. Once an animal is detected, the computer sends a message or signal to the NodeMCU microcontroller. The NodeMCU, which is programmed to handle these signals, responds by taking a specific action, such as triggering an alarm or activating another camera to capture more detailed images. This alert notifies the user or initiates further necessary actions.

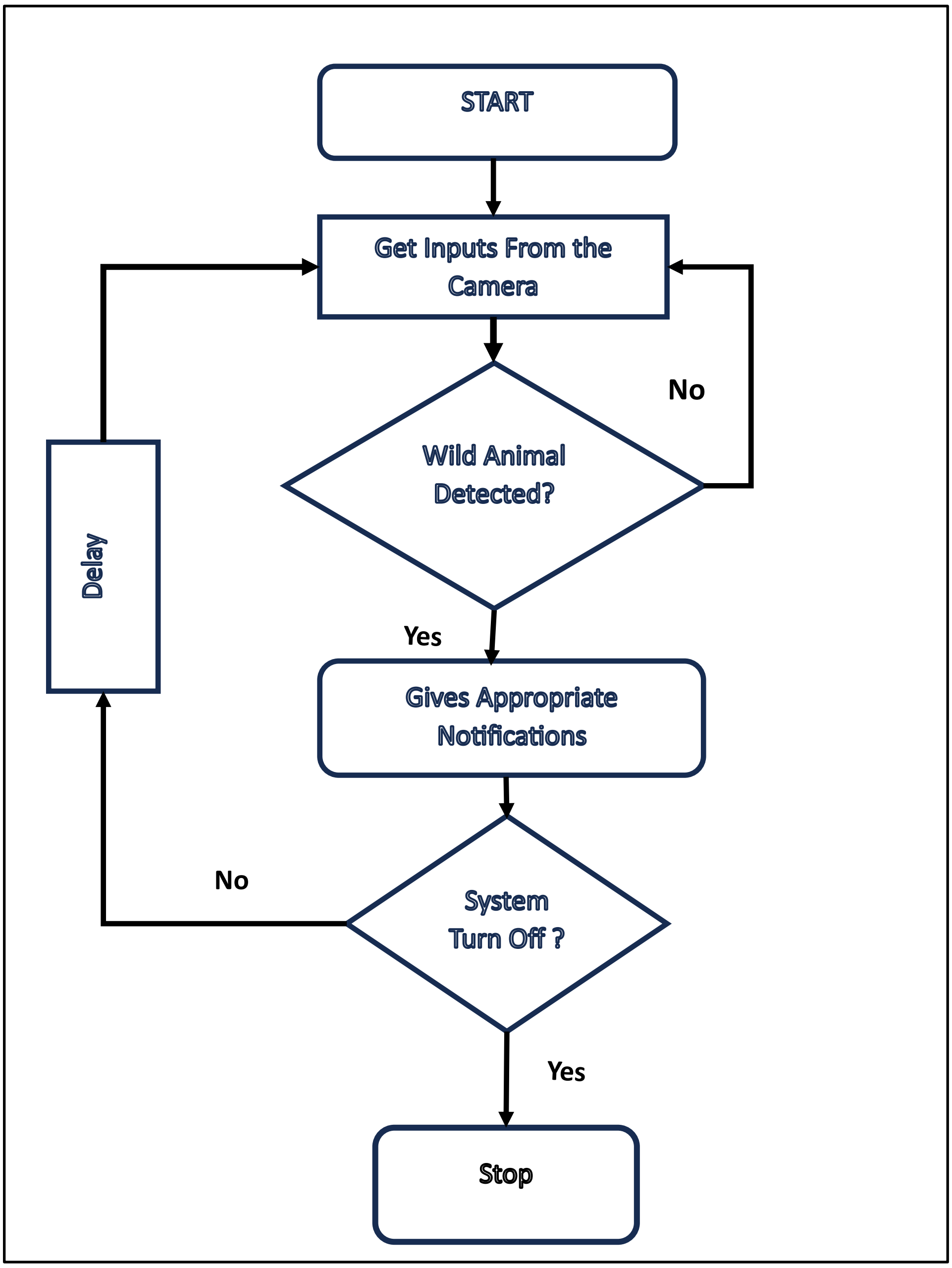
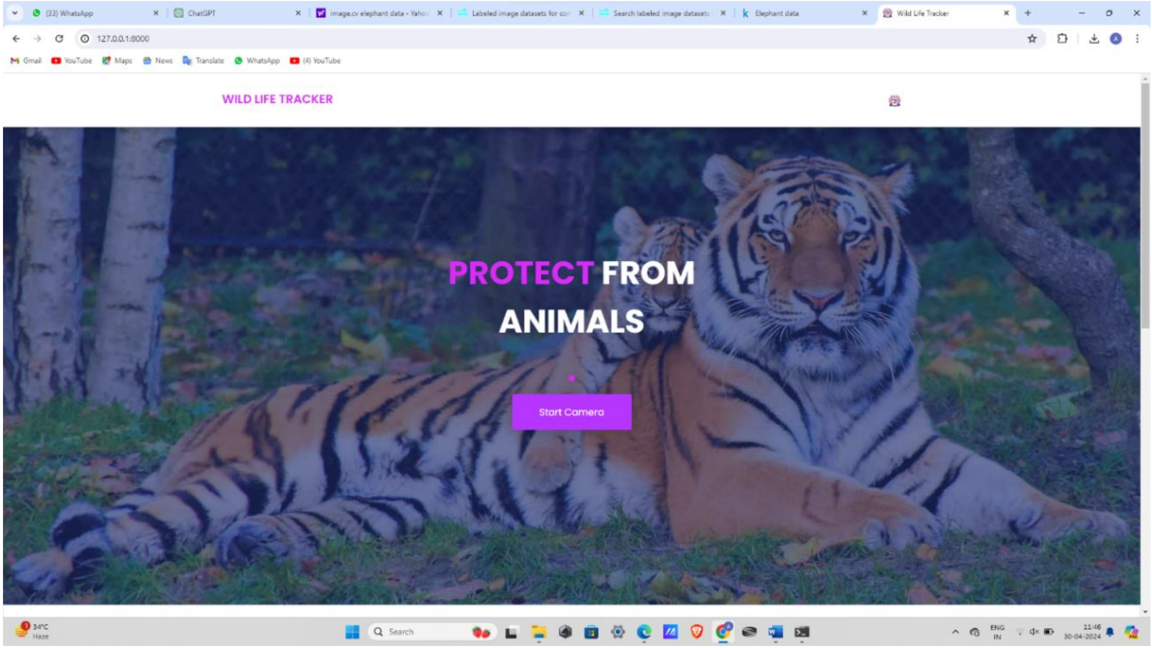


Fig.3 Process Flow Diagram of Proposed Work

5.RESULTS AND DISCUSSIONS

The user interface for our animal detection system generally features a graphical display on the PC screen, enabling users to interact with the system. Through this interface, users can access live camera feeds or review captured images and receive notifications when animals are detected. It may also offer customizable options, such as adjusting detection sensitivity or selecting specific areas of interest within the camera's view. Additionally, the interface might include a log of detected animals, displaying timestamps and possibly corresponding images for later analysis. The overall goal of the user interface is to ensure ease of use, allowing users to efficiently monitor and manage the animal detection system.



Fig,4. User Interface

Animal detection systems discussed here rely on computer vision algorithms to process images or video frames captured by cameras. These algorithms use techniques such as object detection, feature extraction, and machine learning to identify patterns or traits that signify the presence of animals. Common object detection models like YOLO is employed to pinpoint and classify animals in images by detecting specific features or shapes unique to various species. Machine learning models are trained on extensive datasets containing labeled images, which helps improve the system's accuracy and adaptability to different environments and animal types. When an animal is detected, the system can trigger alerts, log the event, or carry out pre-configured actions, aiding in wildlife monitoring, security, and research initiatives.

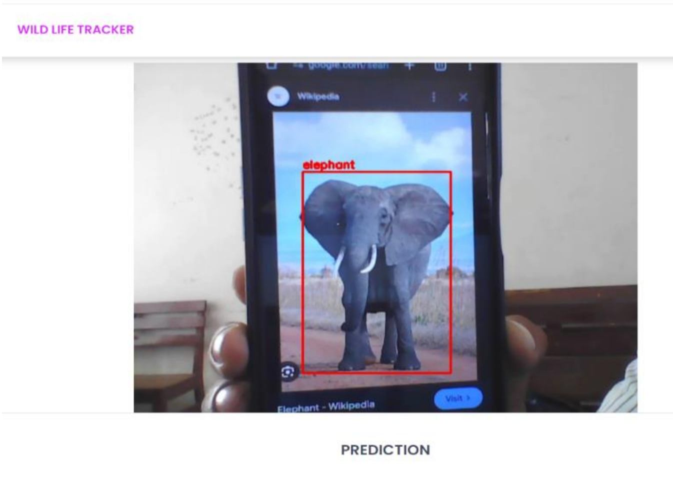


Fig.5 Detection Sample

In our animal detection system, prediction involves utilizing machine learning models to forecast the presence of animals in specific environments by analyzing previous data and identifying learned patterns. These models are trained on labeled datasets that include images or video frames where animals are annotated, enabling the system to recognize visual features and characteristics associated with different species. Once the model is trained, it can examine new images or video streams and predict the likelihood of animals being present. Predictions are typically made by assigning confidence scores to detected objects or regions within the input data, with higher confidence scores indicating a greater probability that an animal is in that area. These predictions are useful for real-time monitoring, alerting users when animals are likely present, and supporting data collection for wildlife research and conservation. Overall, prediction capabilities allow for proactive responses to potential animal activity, improving situational awareness and enabling better decision-making in wildlife detection and monitoring.

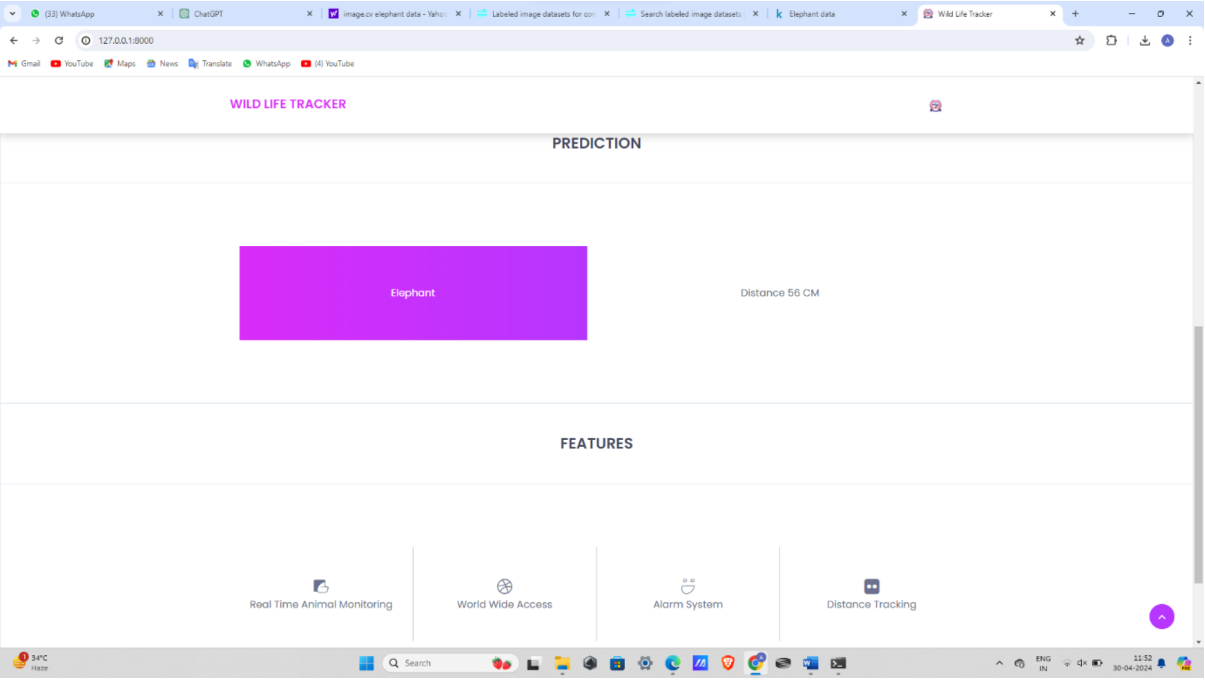


Fig.6 Prediction

6.CONCLUSION

The integrated system discussed here marks a major breakthrough in tackling the ongoing issue of protecting crops from animal intrusion in agriculture. By combining Internet of Things (IoT) technology with Machine Learning, this system offers a strong and automated solution to enhance farm security. This combination allows for real-time monitoring and intelligent decision-making, enabling farmers to manage and reduce potential threats to their crops more effectively. Additionally, the system's adaptability and user-friendly design make it a practical tool for farmers, ensuring that even those with limited technical knowledge can easily adopt and benefit from it. The successful incorporation of these technologies not only strengthens crop protection but also demonstrates an innovative approach to utilizing advanced technology for sustainable and efficient agricultural practices.

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