RakshaNetra: Real-Time Animal Detection & Alert Platform

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Abstract*—Human wildlife conflict is rising as natural habitats shrink and human settlements move closer to forest areas. Wild animals like elephants, leopards, and wild boars often enter villages and farms, leading to crop damage, property loss, and dangers to human safety. Many existing monitoring methods do not provide timely alerts, which results in delayed responses during intrusion events. This paper presents RakshaNetra, a real-time animal intrusion detection and alert system based on deep learning and edge computing. The system continually monitors live video feeds from surveillance cameras. It uses an object detection model to identify and classify wild animals in real time. When it detects an intrusion, it sends instant alerts with images and timestamps to the relevant authorities for quick action. Experimental evaluation shows that the system performs reliably in different lighting and environmental conditions. RakshaNetra offers a cost-effective, non-invasive, and scalable solution to help reduce human wildlife conflict and improve safety in forest-border areas.

Index Terms*—Human wildlife conflict, Animal intrusion detection, Deep learning, Computer vision, Edge computing, Real-time alert system.

I. INTRODUCTION

Human–wildlife conflict has increased in recent years as forest habitats continue to shrink and human settlements expand closer to wildlife regions. Animals such as elephants, leopards, and wild boars frequently enter villages and agricultural lands, leading to crop damage, loss of property, and serious risks to human life, while also posing challenges to wildlife conservation efforts [1], [11]. Traditional monitoring approaches, including physical fencing, manual surveillance, and camera traps, often fail to provide real-time alerts, which limits timely response during intrusion events [2]. Recent advancements in computer vision and deep learning have made real-time animal detection more accurate and practical for outdoor environments [4], [6]. This paper presents RakshaNetra, an edge-based real-time animal intrusion detection and alert system. The system continuously monitors live video feeds, accurately detects and classifies wild animals, and immediately sends alerts with images and timestamps to authorities for rapid action. Experimental evaluation demonstrates consistent performance under varying lighting and environmental conditions. RakshaNetra offers a simple, cost-effective, and non-invasive solution to help reduce human–wildlife conflict and improve safety in forest-border regions.

The proposed system is suitable for deployment in forest-border and agricultural regions where early detection is essential. Edge-based processing reduces response time and minimizes dependence on continuous internet connectivity, enabling faster alerts and reliable operation in remote areas. Similar edge- and IoT-based approaches have proven effective for real-time wildlife monitoring and intrusion mitigation [1], [4], [10], [13].

II. LITERATURE REVIEW

Many people are interested in blockchain technology because it can make supply chain management (SCM) more open, safe, and efficient. Early studies showed that decentralized ledgers can reduce reliance on centralized databases. They provide unchangeable transaction records that build trust among all parties involved (Mansfield-Devine, 2017) [1]. Later studies revealed that using smart contracts with blockchain to automate important parts of the supply chain, like managing orders, tracking inventory, and making payments, can help cut down on human errors and speed up operations (Chen et al., 2018) [2]. Modern blockchain-based SCM platforms like VeChain (2015)

and WaltonChain (2016) connect products throughout their journey in the supply chain [3], [4]. This allows real-time visibility for all participants, ensuring products move smoothly from raw material suppliers to end consumers while reducing the risk of fraud or counterfeiting. However, challenges such as cost, technical complexity, and system compatibility still exist (Lu, 2018) [5].

More recent developments focus on using tools like Ethereum, Truffle, MetaMask, and Web3.js to strengthen and improve supply chain networks (Wang et al., 2019) [6]. Platforms like Ambrosus (2017) and OriginTrail (2013) demonstrate how blockchain can monitor product conditions in real time, share data across organizations, and enhance accountability [7], [8]. Researchers also stress that making these systems easy to use, with secure access and automated smart contracts, is vital for broader adoption (Wang et al., 2020) [9].

Overall, these studies underline the significant potential of blockchain to transform supply chain management. They offer a strong basis for projects like ours, which aim to combine entity registration, smart contract automation, and real-time product tracking to create more transparent, secure, and efficient supply chains.

III. SYSTEM FEATURES AND FUNCTIONALITY

RakshaNetra is designed to reduce human-wildlife conflict by enabling continuous surveillance of forest borders and village boundaries through real-time animal detection and alert generation. The system combines computer vision, deep learning, and edge computing to provide timely and reliable notifications to forest officials. This allows them to take preventive action before dangerous situations develop. Recent studies have also explored similar AI-driven wildlife monitoring and intrusion detection methods [1], [3], [5]. Below are the key features of the proposed system.

A. Real-Time Animal Detection Using AI

RakshaNetra uses a deep learning object detection model, YOLO, to identify wild animals, including elephants, leopards, and wild boars, from live video feeds. The model processes each frame in real time and highlights detected animals with bounding boxes. This method aligns with recent deep learning wildlife detection systems that show high accuracy and real-time performance in challenging environments like low light and partial obstruction [4], [8], [11].

B. Animal Identification and Confidence Assessment

After detection, the system classifies the detected object into a specific animal category and assigns a confidence score to each prediction. Confidence-based filtering helps minimize false positives caused by environmental factors such as moving plants or shadows. Similar classification and confidence assessment methods have been shown to improve reliability in wildlife monitoring systems [2], [6].

C. Instant Alert Generation

When the system detects an animal intrusion, RakshaNetra automatically creates real-time alerts and sends them to forest officials and local authorities. Each alert contains essential information like the animal type, timestamp, and a captured image. This real-time notification process supports quick responses and corresponds with existing IoT- and AI-based alert systems designed for wildlife intrusion management [7], [15].

D. Live Monitoring Interface

The system features a live monitoring interface that displays real-time camera footage along with detection results. Bounding boxes, animal labels, and predefined boundary lines overlay the video stream, allowing authorities to visually assess intrusion events and monitor animal movement effectively. Similar visualization methods are commonly used in real-time wildlife surveillance and camera monitoring systems [3], [11].

E. Event Recording and Analysis

RakshaNetra logs all detected intrusion events along with related data, including images, timestamps, and identified animal species. This stored information supports post-event analysis, movement pattern identification, and future model improvements. Event logging and historical analysis are recognized as crucial parts of intelligent wildlife monitoring systems [10], [13].

F. Scalable and Field-Ready Design

The proposed system is built to be scalable and ready for deployment in real-world scenarios. It allows for the integration of additional cameras and monitoring

nodes without major structural changes. By conducting detection on edge devices, RakshaNetra ensures low latency and operational reliability even in remote areas with limited network access, which is consistent with recent discussions on fog- and edge-based wildlife monitoring systems [1], [10], [13].

The use case diagram shows how RakshaNetra interacts with forest officers. The system captures live video, detects wild animals, and automatically sends alerts. Forest officers receive and review these notifications to take timely preventative actions, as supported by earlier intelligent intrusion detection models [5], [7].

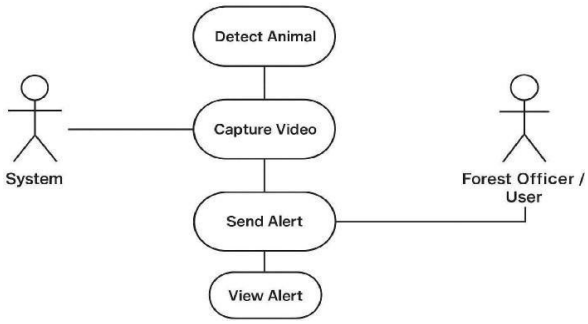

Fig 3.1: Use Case Diagram

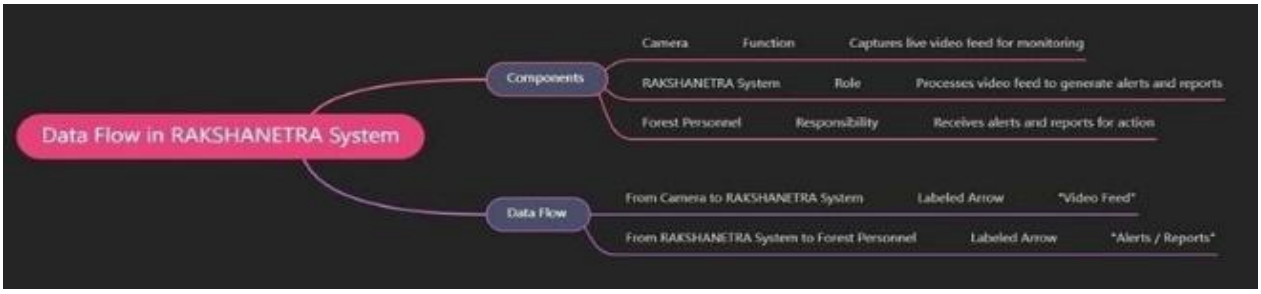

Fig 3.2: Data Flow of System

The data flow diagram illustrates the internal flow of information within RakshaNetra. Live video input from the surveillance camera is processed by the detection module. When it identifies an intrusion, alerts and reports are generated and sent to forest personnel, ensuring timely awareness and quicker responses in critical situations [3], [10].

IV. METHODOLOGY

The methodology of RakshaNetra focuses on creating a real-time animal detection and alert system using deep learning and edge computing to reduce human-wildlife conflict. The proposed approach follows a clear process that includes data collection, preprocessing, model training, and performance evaluation. This is similar to AI-driven wildlife monitoring systems mentioned in recent studies [1], [3], [8].

A.Data Collection and Preparation

The data collection phase involves gathering images and video sequences of wild animals that often cause intrusion incidents, such as elephants, leopards, and wild boars. Data comes from publicly available wildlife datasets and field inputs obtained with help from Pilikula Biological Park. This ensures a realistic representation of forest and boundary environments. The dataset includes samples captured in different lighting conditions, such as low light and at night, which are vital for real-world use [11]. The collected data is screened to eliminate irrelevant or damaged samples and organized by animal categories to maintain consistency and reliability before training [6]. monitoring systems reported in recent literature [1], [3], [8].

Fig 4.1: Dataset Collection (Pilikula Biological Park)

B.Data Annotation & Preprocessing

Annotated datasets are created by manually labeling animal instances with bounding boxes for supervised learning. Preprocessing steps include resizing images,

normalizing data, and reducing noise to standardize the input dimensions needed by the detection model. Data augmentation techniques, like rotation, flipping, and adjusting brightness, help improve robustness against changes in the environment, such as dense vegetation and partial occlusion [2], [4].

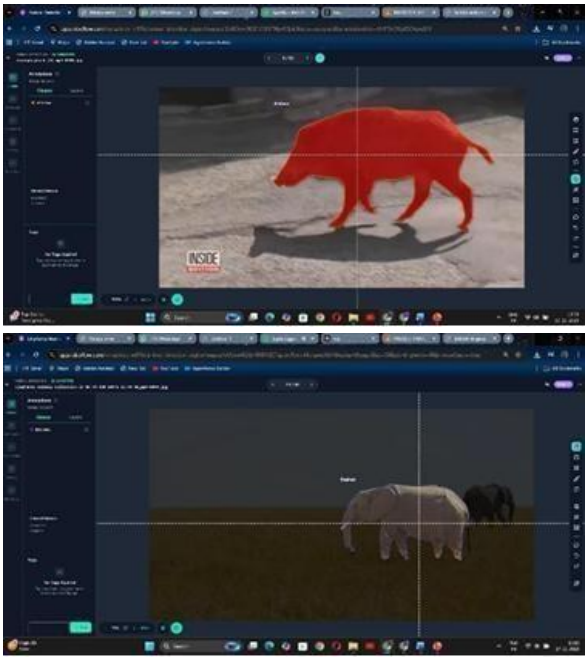

Fig 4.2: Dataset Annotation & Preprocessing

C. Training and Selecting Models

The object detection model used by RakshaNetra is based on the popular YOLO architecture because of its ability to provide very accurate detection results in real-time with low inference latency [4],[8]. In addition, RakshaNetra uses transfer learning to improve on an already trained YOLO model by applying a pre-trained weight from a different dataset to create a new model based on the wildlife dataset created for the project. The new YOLO model created using transfer learning is then deployed and run on an edge device (Raspberry Pi) to make use of the ability to do inference without the use of a cloud-based model. The edge deployment configuration is consistent with the use of fog and artificial intelligence of things (AIoT) to detect wildlife intrusion using previously discussed technologies [1],[10].

D. Assessment of Model Performance

The system will be evaluated using standard object detection performance metrics including accuracy, precision and recall to determine the level of reliability for the detection of suspected intrusions and the false alarm rate of the overall system [11]. Also recorded will be the time to complete the inference of the model as well as the total time for the system to alert the authorities. Both metrics are critical for determining if the performance of the deployed edge devices running the model is suitable for real-time detection of suspected wildlife intrusion. The performance of the overall system will also be evaluated with respect to environmental conditions including solar energy and weather to establish that RakshaNetra will continue to perform reliably in a continuous fashion throughout the operational period in forest-border areas [3],[15].

V. PROTOTYPING AND DASHBOARD DESIGN PROCESS

A. Hardware Requirements

To ensure effective, dependable, real-time identification of wildlife in low-light and remote areas, the RakshaNetra project will require the use of a robust hardware platform. This includes, at a minimum, a night vision surveillance camera which will allow continuous monitoring of wildlife at night and/or in low-visibility conditions. In addition, the installation of one or more 360° cameras may be considered to provide full coverage of the village's border, or peripheral to a forested area. In order to execute a locally deployed animal-identification model (animal-detection model), an edge computing device, such as the Raspberry Pi (or equivalent) shall be used so as to minimise latency and reliance of cloud infrastructure. The utilization of an edge-based solution will therefore create greater responsiveness and reliability, particularly in more remote areas that experience limited connectivity, as evidenced by the success of previously implemented AIoT wildlife monitoring solutions [1], [5], [10].

B. Software Requirements

The software infrastructure will provide a real-time processing capability and generate notifications. The Raspberry Pi will run the Raspbian Lite operating system because it is light and reliable. The Python 3.x programming language will be used as the primary programming language for all of the software. OpenCV will be used for stream handling and frame pre-processing from the video camera. The YOLOv5 framework will be used for detecting and classifying

animals in real-time based on the compromises between speed and precision [4], [8]. NumPy will be used for numeric computations, and Matplotlib will be used to visualise and analyse the results. The integrated Telegram Bot API will be used to send notifications, including pictures, and detection data, to local government officials or village authorities, thus allowing for rapid response [7], [15].

C. *Functional Requirements*

RakshaNetra's video surveillance collects live streams from the surveillance camera and triggers on motion so as to minimize unnecessary processing. When an event of motion is detected, frames are extracted from the image and the YOLOv5 model is employed to both detect and to classify wildlife. When an intrusion occurs, real-time alerts containing the type of detected animal, the image of that animal, the date, and the time are generated. In addition, all detection events are stored locally for use in analysis, review, and improvement of the system. The entire functional workflow contains all elements that would allow for a proactive monitoring capability and a successful mitigation of human–wildlife conflict, which is consistent with previously established automated intrusion detection systems [3],[6],[11].

D. Non-Functional Requirements

The system has been designed to be reliable so that it operates continuously with no or very little downtime; the usability of the system has been prioritised so that automation of execution can occur with minimal manual intervention after deploying the system; the system has a maintainability feature allowing for periodic retraining of the models (e.g., via model retraining) as well as software updates (e.g., new animal classes or environmental conditions) incorporated into the system via these updates. In addition, the system architecture is designed so that it can support scale and integration of additional cameras or detection nodes in much larger geographic regions, which corresponds to distributed wildlife monitoring systems recently proposed in IoT and deep learning literature [10],[13]

E. Performance Requirements

The performance expectations for RakshaNetra include detecting and classifying animals within 2-5 seconds of the camera capturing an image (under normal conditions). Additionally, alert notifications must be sent within 10 seconds of detection to allow timely preventive action. In addition, the overall accuracy of the system when detecting commonly occurring wild animals (elephants, leopards, wild boars, etc.) will be required to equal at least 80% as shown in similar deep learning-based systems [8],[11]. Assuming a stable power supply, and network connectivity, the target uptime for the RakshaNetra system is over 95%; therefore, it will be appropriate for wildlife sensitive areas, and therefore these systems can be used in real time to provide critical monitoring.

VI. EXPERIMENTAL RESULTS

A. Dashboard Implementation

RakshaNetra provides an interface for forest authorities and others to view live images cameras placed at thresholds between forests and neighboring villages.

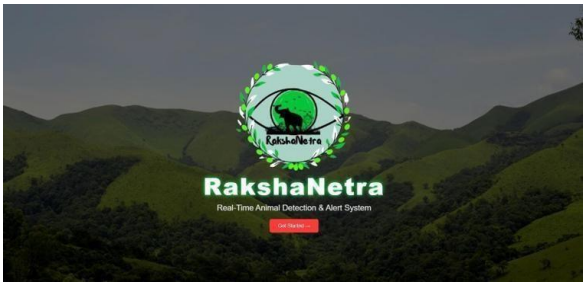

Fig 6.1: Landing Page

The video feed provides users with a simple and real-time view of detected animals on the video, with bounding boxes around them, showing species and the status of the animal in relation to the threshold. Such information allows the users to readily understand the current status of the animals and react quickly. Access to the dashboard is also restricted to only those personnel who have been authorised to view alerts and outputs from the system.

B. Real-Time Animal Detection and Intrusion Analysis

RakshaNetra utilises a deep learning model to detect and provide real-time reporting using video streaming as the input. RakshaNetra has been designed to detect wildlife, including elephants, leopards, and wild boars, by using YOLO-based algorithms to determine if there is any wildlife detected in video footage; if so, a bounding box and confidence score are displayed for

each animal detected in the video;ıy;ı. The system is able to provide consistent results when dealing with challenging circumstances that affect the quality of the footage, including conditions such as low lighting, limited visibility, and/or the amount of vegetation in the surrounding area.

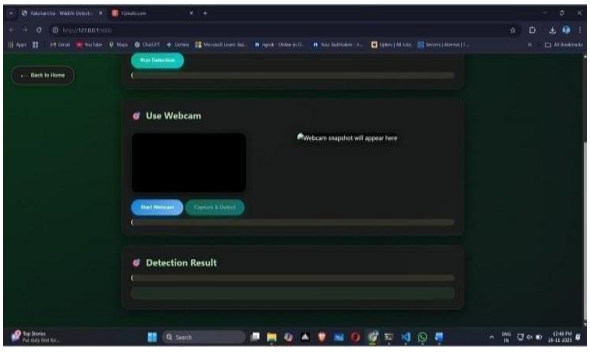

Fig 6.2: Live Monitoring Dashboard

C. Automated Alert Generation and Notification

RakshaNetra automatically sends Forest Officers an alert whenever an animal crosses an established boundary. Each alert contains information such as what type of animal was detected, when it was detected, and an image captured through the live feed. During the tests conducted, alerts were sent within a few seconds of being detected, which provided the authorities enough time to respond prior to the occurrence of an incident. Due to this rapid alerting system, response times are shortened and overall awareness is improved in areas where there are frequent encounters between humans and wildlife.

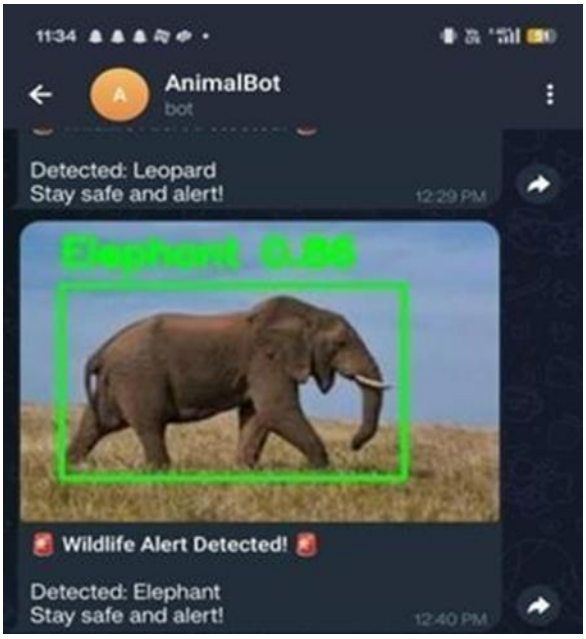

Fig 6.3: Intrusion Alert – Telegram Notification

D. System Performance and Observations

The experiment conducted using both real-time (live) camera images as well as previously recorded video of wildlife, under various lighting and the physical environment. RakshaNetra exhibited smooth, stable performance on the edge devices used for testing. Accurate detection, as well as minimal latency, were achieved during the tests. The elimination of false detections was accomplished through the utilization of confidence thresholds. The consistency of system performance allowed RakshaNetra to maintain reliability even after extended monitoring periods. \par \par Overall, the results from the experiment demonstrate that RakshaNetra is a viable, reliable tool for practical use in the field of forest border surveillance.

VII.CONCLUSION

This research presented a novel approach (RakshaNetra) for efficiently detecting and alarming wildlife intrusions through deep learning and edge computing. A night-vision surveillance camera positioned on a Raspberry Pi-based edge device was used to enable real-time identification of animals using a YOLO model with low latency processing for deployment in remote forest and village environment boundaries [1], [5], [8]. The use of automated alerts provides timely alerts back to users for effective intervention by authorities [7], [15]. Additionally, the results from the experiments demonstrated significant levels of accuracy and response rates regardless of the changing environmental conditions, corroborating

earlier studies in wildlife monitoring [3], [11]. Thus, RakshaNetra provides a cost-friendly, scalable, and reliable solution, showing how the application of artificial intelligence (AI) and internet of things (IoT) technologies can be practically used for real-world scenarios involving the monitoring of wildlife intrusions

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