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WILDLIFE SAFETY AND HUNTER MONITORING SYSTEM USING AI CAMERAS AND GEOFENCING FOR REAL-TIME ALERTS

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Abstract :

A real-time wildlife safety and hunter monitoring system that integrates AI-powered cameras with geofencing technology to enhance wildlife protection and prevent illegal hunting. In this research, a wild animal safety and hunter monitoring system that leverages advanced deep learning techniques of specifically YOLOv11 for object detection, and a deep Convolutional Neural Network of CNN for classification and feature refinement to enhance wildlife protection. The proposed system deploys AI-powered cameras across forest and buffer zones to automatically detect humans. The wild animals and hunting-related activities are shown in real time. YOLOv11 is utilised to perform fast and accurate detection of objects such as hunters, weapons, and animals under varied lighting and environmental conditions. The detected result as an output is further processed by a Deep CNN for fine-grained analysis. To ensure robust identification and reduced false alarms. The integration of geofencing allows the system to distinguish between legal hunting zones and restricted areas. To enable intelligent activity such as decision-making. When unauthorised activity is recognised, the system triggers immediate alerts to authorities through a centralised monitoring system. By combining the high-speed detection capabilities of YOLOv11 with the deep feature extraction power of CNN. This system provides a scalable, real-time time and reliable solution for wildlife conservation and anti-poaching efforts. The experimental result demonstrates that the proposed system achieves an overall accuracy of 95.6% to confirming its reliability and effectiveness in monitoring wildlife and detecting illegal hunting activities.

Keywords: Wildlife safety, Hunter monitoring, YOLO11, Deep Convolutional Neural Network, Object detection, Real-time monitoring, poaching prevention, AI-powered surveillance.

1. INTRODUCTION

The development of an early warning system for human-wildlife conflict using deep learning of IOT and SMS. It is more evident in the United Republic of Tanzania, whose economy depends on agriculture and wildlife tourism as a significant source of income for its citizens and foreign exchange, respectively.

This system was developed using open source, using a Raspberry Pi, which is cost-effective even for low-income communities that target the system. Therefore, the system detection to identifies and reports wild animals detected using SMS [1]. AI-enhanced IOT integrated virtual fencing, a proof of concept for camel monitoring and collision mitigation. In a desert region has increased camel vehicle collisions have resulted in a substantial human economic and animal welfare impact. Despite the success of virtual fencing in managing livestock such as cattle, goats, and sheep and its application for camels remains largely unexplored. This study offers a significant contribution to the field of wireless communication of IoT-based animal management systems [2].

A remote surveillance system based on AI for Animal tracking near the railway track. A Pi camera is properly positioned to record an animal completely crossing a railway track. The cameras send information to the central server, where it is evaluated before being used to notify an interested group of an alert. The real-time danger and unsafe scenarios can be independently identified. This is made possible by the graphics processing unit that is being used to propose a boost in security and safety in various ITS services at railway crossings [3].

The feat of designing and implementing a robot for plant disease detection, animal trespassing detection, and locust prevention. The robot is designed for plant disease detection and animal trespassing detection, and locust prevention [4]. These technologies enable real-time data collection, including high-resolution conservation forensics, the intersection of wildlife forensics and conservation. The poaching and illegal wildlife trade of the wildlife crime are commercialisation and overexploitation of wildlife, crime threaten the biodiversity of many species already cusp extinction. The efforts from wildlife law enforcement to prevent wildlife crime are a conservation necessity of wildlife criminals and the prevent wildlife crime to conserve biodiversity [5].

The wildlife forensic genetics is of tool for resolving wildlife crimes and supporting species conservation. The use of molecular analysis in wildlife forensic genetics has become a key tool for enforcing legislation against these crimes and protecting the flora and fauna. The species are pointed out that despite the vast potential for the application of forensic genetics in wildlife crimes [6]. The wildlife crime: a conceptual integration literature review and methodology critique. The wildlife crime, including poaching and wildlife trafficking, threatens the existence of particular species. The data research in wildlife crime is primarily conducted by those with a background in biological science; however, scientists offer an examination of wildlife crimes [7]. Conservation forensics: the intersection of wildlife crime forensics and conservation. The poaching and illegal wildlife trade of wildlife crime and the global. The commercialisation and overexploitation of wildlife caused by wildlife crime threaten the biodiversity of species already extinct. The wildlife crime also leads to ecosystem collapse and loss of government revenues and threatens the strength and economic development of nations [8]. AN AI-driven monitoring system integrating automated attendance of real-time visitor detection, of facial recognition based on geo-fencing. AN AN-based hostel monitoring system focusing on automatic attendance of real-time visitor detection, of face recognition based on

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geofencing. The research analyses the role of ML in enhancing security and efficiency in hostel management [9].

Creating alert messages based on wild animal activity detection using hybrid deep neural networks. The issue of animal attack is increasingly concerning for rural populations and forestry workers. The track the movement of wild animals, surveillance cameras and drones are often employed. Figure 1 represents an alert message that can detect animal types and monitor their locomotion, and provide their location information [10]

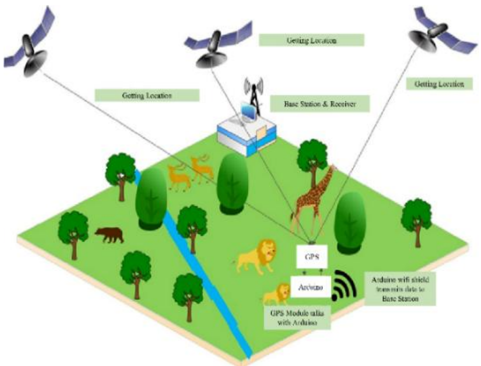

Figure 1: Wildlife safety and hunter monitoring using AI cameras

2. RELATED WORK

In wildlife monitoring and anti-poaching system have been widely studied using computer vision of IOT and AI technologies. Several research works demonstrated the role of the deep learning based object detection model in identifying animals. The human and threats in the natural environment, for instance, of YOLO based models of YOLOv5 and YOLOv7 have been applied to camera trap images for detecting animal species with high accuracy Figure 2. The Deep CNN with image classification tasks has improved detection performance under challenging conditions, such as occlusion of low light and dense vegetation.

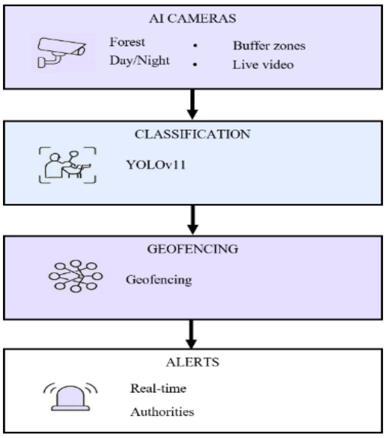

Figure 2: Wildlife safety and hunter monitoring system for real-time alert

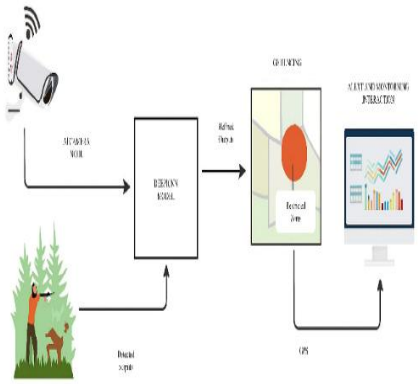

Figure 3: Wildlife safety system

The research introduced a geofencing and GPS-based monitoring system to track wildlife movement and human intrusion. The data combination with mobile alerts has been used in conservation efforts to reduce illegal entry into restricted areas. The recent work highlights the integration of edge AI cameras with IoT-based communication protocols of MQTT, LoRaWAN for real-time wildlife tracking in a remote forest region. Ati's poaching system, such as SMART, stands for Spatial Monitoring and Reporting Tool and acoustic gunshot detection Figure 3. The system often faces limitations like delayed alerts, poor accuracy at night, and a lack of integrated decision-making.

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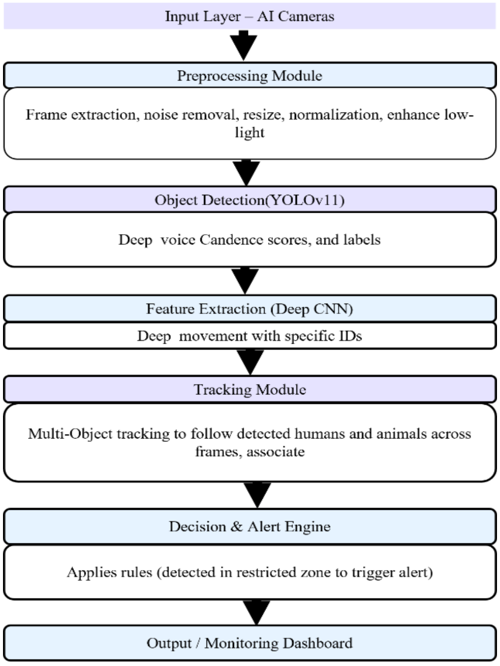

Figure 4: AI-powered monitoring system architecture

The proposed system advances existing systems by combining YOLOv11 for high-speed object detection in a Deep CNN for classification refinement and geofencing for spatial validation. The previous approaches that focus only on detection and tracking, this system provides a real-time and end-to-end solution for wildlife safety and hunter monitoring, with achieved conservation enforcement Figure 4.

3. SYSTEM ARCHITECTURE

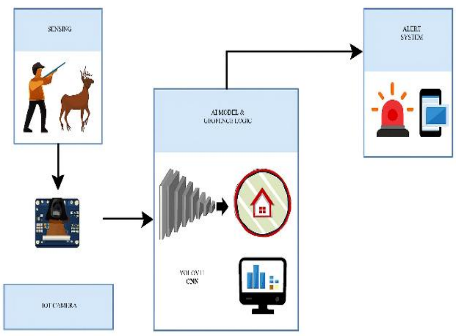

Figure 5: Real-time detection and monitoring of wildlife protection

The above Figure 5 represents a real-time detection and zonal compliance monitoring for wildlife protection. The system under development is a holistic, end-to-end real-time wildlife safety and hunting monitoring solution that employs several technologies sensor network, Object detection by AI, Geofencing, and alert notification and brings them together into one common architecture that can run independently in distant forest regions. The system is designed to identify and categorise wildlife and human presence, determine the legality of their presence based on the geospatial perimeter and initiate instant alerts upon identifying illegal behaviour.

The backbone of the system is a web of AI-enabled camera modules installed throughout forest interiors and buffer zones. They take continuous visual data, which is locally processed with a deep learning pipeline. The object detection model, YOLOv11, detects main objects like wild animals, poachers, and gyns at a high speed and accuracy. To improve detection reliability, YOLO11 outputs are pipelined through a deep Convolutional Neural Network (CNN) for fine-grained classification and feature refinement. This two-stage pipeline ensures strong recognition event under different environmental conditions, such as low light, Occlusionand motion blur.

After objects are identified and categorised, the system performs geofencing logic to decide if the activity is taking place in legal or off-limits areas. The virtual limits are established with the aid of GPS coordinates, enabling the system to dynamically test compliance in space. This feature is vital for differentiating authorised hunting in approved

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locations from unauthorised entry into protected wildlife habitats.

The last phase is real-time alert generation. Whenever abnormal activity is picked up, the system sends the alerts through communication modules like LoRa, GSM and WiFi based on topography and connectivity. The alerts are received by a central monitoring dashboard and can be sent over SMS and mobile app notifications to forest guards and enforcement bodies. This speed of response allows for prompt interventions, thus improving the efficacy of wildlife protection and anti-poaching activities.

4. SYSTEM COMPONENTS

4.1 AI cameras module

The system employs compact AI-powered camera modules such as ESP32-CAM and Raspberry Pi with YOLOv11 for quick and accurate identification of objects. The units are strategies mounted throughout our forest and buffer areas to track wildlife and human movement in real-time Figure 6. YOLOv11 provides strong identification of animals, untef, and guns under Variable environmental conditions. With the ability to process onboard, the cameras function independently, reducing latency and supporting effective monitoring in low-connectivity and remote areas.

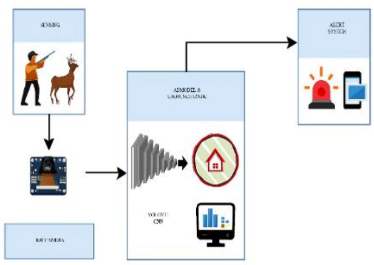

Figure 6: Modular integration of an AI camera

4.2 Geofencing logic

The below Figure 7 shows that the geofencing is a key element of the system under proposal that supports spatial perception and context-aware decision making. It works by establishing virtual perimeters in terms of GPS coordinates that relate to legal hunting areas, protected areas, and buffer zones. These perimeters are maintained in the spatial database of the system and repeatedly referenced when conducting monitoring activities.

Figure 7: Legal hunting

When an object showing the individual weapons of an animal is detected using the AI cameras module, the system captures the GPS points of detection. The location is cross-checked with a geofenced area as defined beforehand to ascertain if the activity is in a given area where it is allowed. All this happened in real-time spatial verification to allow the system to distinguish between approved and disapproved.

The geofencing logic must be dynamic and scalable. The zone definition can be remotely changed by administrators to accommodate seasonal changes, policy updates or emergency restrictions. This enables the system to responde to change conservation strategies and enforcement procedures.

By combining geospatial intelligence with AI-derived detection, the system improves its capability to detect threats like poaching, illegal invasion and encroachment into protected ecosystems. The layered mechanism greatly minimises false alarms and ensures that alarms are issued only when real violations are made, thus enhancing response efficiency and resource allocation.

4 .3 Communication layer

Figure 8: Communication layer architecture

The above Figure 8 represents that secure data transmission is crucial to the success of any real-time monitoring system, particularly in remote and environmentally sensitive regions. The suggested architecture integrates an adaptive communication layer that can support different protocols, LoRa, GSM, and WiFi, to provide uniform connectivity across various terrains and environmental conditions.

LoRa is well-suited to forest and mountain areas where traditional cellular networks can be absent and unreliable. Its long-range, low-power properties enable AI camera modules to send detection data a few kilometres and not need constant battery replacement. This makes LoRa suitable for extended use in wildlife reserves and buffer zones.

4.4 Cloud and edge processing

The system utilises a hybrid processing paradigm that integrates edge and cloud capabilities to realise maximum performance. The local object detection and classification are performed directly on the AI camera module, allowing for low-latency response and minimising network reliance. For high-level analysis and CNN-based feature enhancement, long-term data archiving, specific outputs are offloaded to cloud servers. This two-layer show in Figure 9 facilitates quick decisions within the field with scalable analytics and central monitoring, offering a balance between speed, efficiency and resource utilisation.

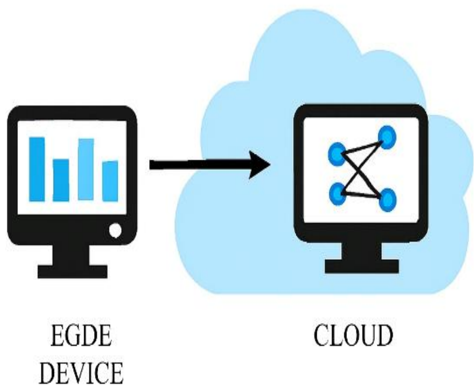

Figure 9: Hybrid cloud and edge architecture

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4.5 Alert delivery system

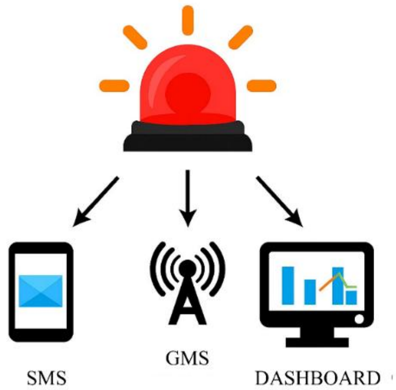

Figure 10: balanced local remote data analysis

The alert delivery system is the last but most essential of wildlife monitoring architecture, converting detection events into effective reactions. After unauthorised activity is confirmed through geofencing logic, the system triggers a real-time alert process Figure 10. Alerts are delivered using a multiple-channel communication system to provide redundancy and reach. SMS alerts are delivered to the registered mobile numbers of forest rangers and enforcement officers for immediate awareness in areas of low bandwidth. The messages usually contain the category of threat of GPS coordinates, and the detection timestamp.

The concurrent push notification in mobile apps provides a richer user interface through the display of images, text. categorisation and zone context. The app is also capable of supporting acknowledgement and escalation business processes, which enable field teams to plan a response effectively.

A centralised dashboard collates all the alerts and visualises system activity in monitored zones. The dashboard is accessible by secure login and offers real-time analysis, historical logs and zone-wise threat mapping. It enables supervisory teams to monitor trends, assign resources and authenticate field actions.

Through the integration of different alert channels, the system provides high reliability and responsiveness. The multi-layered approach increases situational awareness, minimises reaction time and enhances enforcement capabilities in wildlife protection operations.

5. PROPOSED METHODOLOGY

The proposed methodology of wildlife safety and hunter monitoring system that combines AI-powered cameras of YOLOv11 object detection using a Deep Convolutional Neural Network (CNN) and geofencing to provide real-time monitoring and alerts, Figure 11. The high-speed detection of robust classification and spatial validation to minimise false alarms and to improve conservation enforcement.

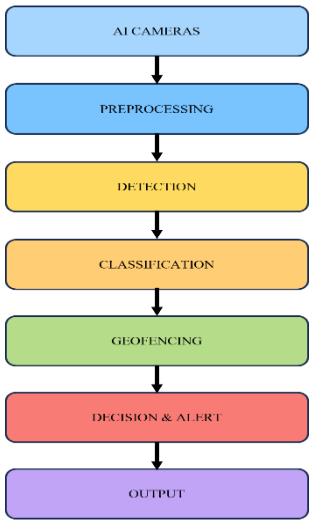

Figure 11: Wildlife safety and hunter monitoring of geofencing for real-time

$$LYOLO = \lambda_{coord} \sum_{i=1}^{S^2} \sum_{j=1}^{B} 1_{ij}^{obj} \left[(a_{ij}^{x} - \hat{a}_{ij}^{x})^2 + (a_{ij}^{y} - \hat{a}_{ij}^{y})^2 \right] \quad (1)$$

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Equation (1) shows that the training loss of YOLO style total loss of the general form. The YOLO losses combine bounding box regression objectives and classification terms in a common form. S indicates grid size, B indicates box per cell, bij indicates b^ij predicted box, and λ indicates weighting hyperparameters.

$$L_{CE} = -\frac{1}{M}\sum_{n=1}^{N}\sum_{k=1}^{K} y_{n,k} \log \hat{y}_{n,i} \quad (2)$$

Equation (2) indicates the CNN classification loss of cross-entropy of the CNN that classifies crops into classes of the hunter, tourist, animal, and weapon. N indicates the number of batches, and k indicates the number of classes.

$$L_{total} = L_{YOLO} + \alpha 1 L_{CE} + \beta 1 L_{reg} \quad (3)$$

Equation (3) shows a combined training objective of joint sequential and if jointly fine-tune and combine losses. α,β indicate that the balanced terms of optional regularisation of weight decay.

$$C_{fused} = \omega_{yolo1} + C_{yolo1} + \omega_c + C_{CNN} \quad (4)$$

Equation (4) indicates that the weighted confidence fusion of YOLO confidence detection and CNN softmax probability for the same class confidence. The final detection of the threshold tune on the validation set.

$$I_{OU}B(A,B) = \frac{area(A \cap B)}{area(A \cup B)} \quad (5)$$

Equation (5) represents a non-maximum suppression of NMS to remove overlapping boxes and keep the box with the highest cFused, and to remove others with IOU above tnms.

$$\Delta\emptyset = \emptyset_{22} - \emptyset_{11}, \ \Delta\lambda = \lambda_{22} - \lambda_{11} \quad (6)$$

Equation (6) represents the haversine distance of the distance-based geofence of the given two lat-long pairs of (ϕ1,λ1) and (ϕ2,λ2) in radians.

$$a = sin^2\frac{(\Delta\emptyset)}{2} + cos\emptyset_1 cos\emptyset_2 sin^2\frac{(\Delta\lambda)}{2} \quad (7)$$

$$d = 2S\ arctan2\left(\sqrt{a}, \sqrt{1-a}\right) \quad (8)$$

Equation (7) indicates that R is Earth's radius of 6371 km, and if d is greater than the radius of the geofence radius of point is inside the circular fence.

$$1_{inside}(Q) = \begin{cases} 1, if\ P\ is\ inside\ the\ polygon \\ 0\ , \quad Otherwise \end{cases} \quad (9)$$

Points in polygon of winding of ray casting for polygon geofence vertices V and points P to use ray casting to count the ray intersections with polygon edges of odd inside.

$$Alert1 = 1\left(C_{fused} \geq \tau\right) \cdot 1_{restricted}(P)\big) \quad (10)$$

Equation (10) indicates that the alert rule of the logic form of an alert is raised when the detection exists. The fused confidence is greater than, and a geofence indicates a restricted area

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

$$mAP1 = \frac{1}{K}\sum_{k=1}^{K} AP_{k1} \quad (12)$$

Equation (11) and (12) represents the precision and recall of the F1 score. The mean average precision of mAP is used to compute the average precision of AP per class from the precision and recall curve, and then typically uses an IOU threshold of mAP of 0.5.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (13)$$

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Equation (13) represents the accuracy of reporting a single number of the report's overall classification accuracy of alarms.

$$T_{total} = T_{yolo1} + T_{CNN1} + T_{comm} \quad (14)$$

Equation (14) represents a detection latency of real-time constraint of YOLO inference time and CNN refinement time, and communication overhead of the total latency of real-time.

The system comprises four integrated components, such as an AI camera node, a Deep CNN module, a Geofencing engine, and an Alert dashboard. The AI camera node denotes the capture of real-time footage in the forest and buffer zones. The Deep CNN module indicates that it refines the object detection output for improved classification. The Geofencing engine shows that the validates spatial legality using GPS boundaries. The Alert dashboard represents a centralized interface for monitoring and response. Figure 12 represents a proposed system that integrates AI-powered edge cameras and other components of infrastructure to enable real-time wildlife safety and hunter monitoring components.

5.1 Integrated system design

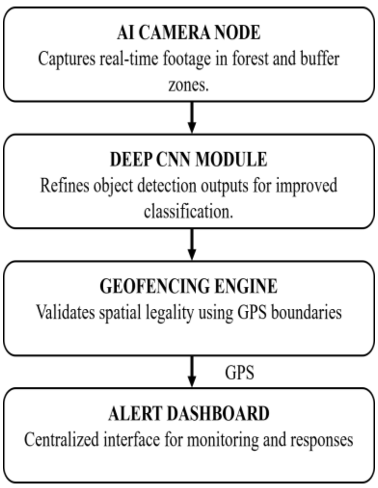

Figure 12: Hunter detection system layout

5.2 Object detection with YOLOv11

The Object detection with the YOLOv11 algorithm shows a transformed backbone of anchor-free detection and an adaptive attention mechanism. The high-speed detection of hunters with weapons and animals. The robust performance under occlusion of low light and a cluttered background. The real-time inference on the edge device, as shown in Figure 13, shows.

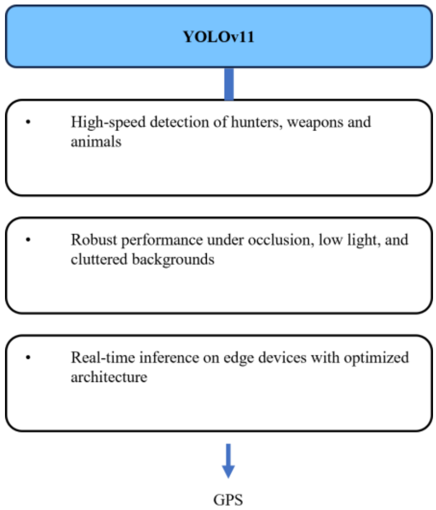

Figure 13: Object detection with YOLOv11

5.3 Feature refinement with deep CNN

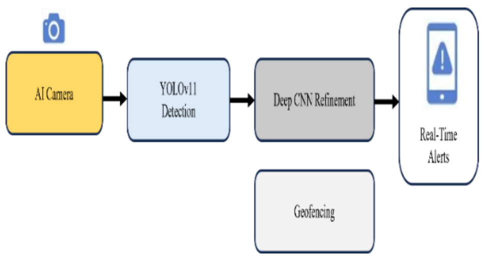

Figure 14: Proposed system architecture of object detection with YOLOv11

The post-detection of deep convolutional neural network performance of fine-grained classification of detected entities to distinguish hunters from tourists. The feature enhancement using CBAM of Convolutional Block Attention Module for spatial and channel-wise attention. The Reduction of false positives through multi-layer validation, Figure 14,15.

5.4 Geofencing and spatial validation

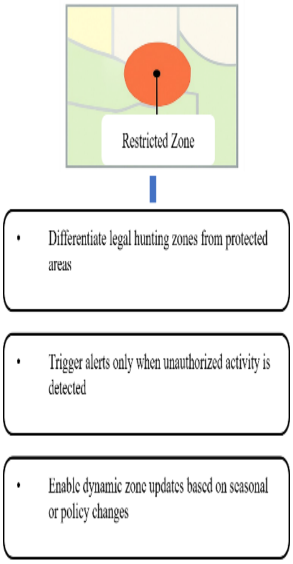

Figure 15: Geofencing and spatial validation

The geofencing module integrates GPS data to differentiate legal hunting zones from protected areas. The trigger alerts only when unauthorised activity is detected. Enable dynamic zone update based on seasonal and policy changes. The geofencing module plays a critical role in spatial awareness and enforcement within the wildlife monitoring system. The use of GPS coordinates to create virtual boundaries that define legal hunting zones and protected areas. The AI system detects human activity of the geofencing engine to check whether the location falls within a permitted zone Figure 15. The legal restricted zones are a system that compares detected locations against predefined geospatial boundaries to determine legality. The alert triggers are only active when activity occurs in restricted zones, minimising false positives.

5.5 real-time alert system

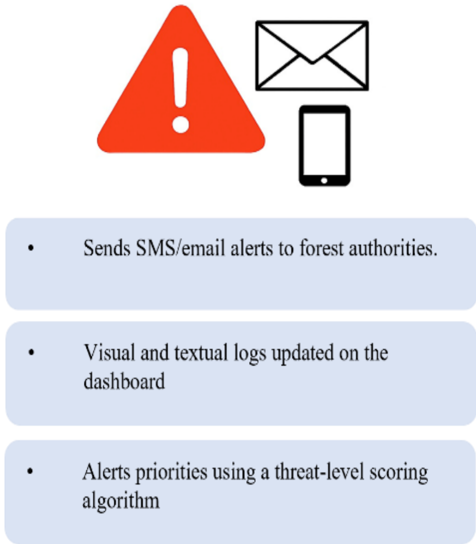

Figure 16: Real-time alert system

5.6 Communication protocols

Figure 17: Communication protocol for real-time wildlife monitoring

The reliable data transmission across the remote forest region and the system employs a combination of lightweight IoT protocols and edge computing methods. The MQTT of Message Queuing Telemetry Transport of a lightweight protocol ideal for low-bandwidth environments. This enables fast real-time messaging between AI camera nodes and the central dashboard with minimal overhead. The LoRaWAN of Long Range Wide Area Network is used for transmitting

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data over long distances in remote areas where cellular and wifi coverage is limited Figure 17. It supports low-power devices and ensures connectivity in rugged terrains.

6. PERFORMANCE METRICS

Class	Precision	Recall	F1 score	Support
Hunter	0.96	0.94	0.95	1200
weapon	0.93	0.91	0.92	500
Wild animals	0.97	0.96	0.96	2000
Domestic animals	0.90	0.88	0.89	300
Average	0.94	0.93	0.94	4500

Table 1: Dataset summary table

The above Table 1 represents a data source of training and evaluation that was collected from a camera trap device installed in forest zones. The supplement with custom field captures to ensure diversity. To provide realistic data on the reflected environmental condition in which the system will be deployed, Figure 18. The total images of 18000 with the label of images in the dataset provides enough variation to reduce overfitting.

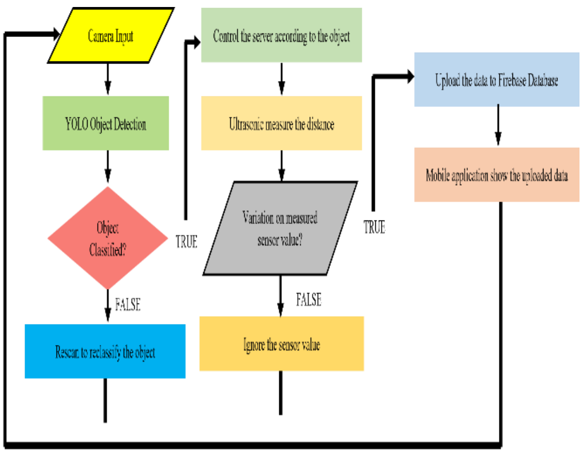

Figure 18: YOLO object detection system

Data Item	Description
Source	Camera trap images and custom field captures target
Frames	18000
Labels	Hunter, weapon, wild animals
Approx	Human, domestic
Environmental condition	Low light, rain

Table 2: Model performance metrics

The above Table 2 represents the detection and classification performance of the proposed YOLOv11 and Deep CNN of the hybrid system across all classes. The evaluation of user precision, recall, and F1 score of the metrics of the computer classification task. The human as a hunter's precision of 0.96 when the model predicts the hunter to correct 96% of the time. The recall of 0.95% of all actual hunters of data, 94% of detection. The F1 score of balanced precision and recall of the high reliability of detection and hunter monitoring. The weapon of precision of 0.93 and recall of 0.91 indicates the lower performance compared to human detection. The weapons may appear small, camouflaged, and partially occluded, making them harder to detect.

The following Table 3 represents a YOLOv5 baseline with a precision is equal to 86.2% and recall of 82.5% and an F1 score of 84.3%. The baseline of YOLOv5 performance is reasonable, but it struggles under the challenging conditions of occlusion and low light. The alarm of an accuracy is equal to 80.7% of means false alarms are relatively high and reduce reliability for real-world monitoring. The improvement over YOLOv11 and deep CNN is the proposed method of precision 93.8% and recall of 92.0% the highest across all models.

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Model	Precision percentage	Recall percentage	F1 score percentage	mAO@0.5	Alarm accuracy	Average time
baseline	56.2	82.5	84.3	81.4	80.7	45
YOLOv7	88.7	84.9	86.7	84.6	83.9	40
Detection only	90.1	86.5	88.3	87.2	86.0	38
Proposed model	93.8	92.0	92.9	91.7	95.0	0

Table 3: Performance Comparison

7. FUTURE SCOPE

Figure 19: Wildlife conservation strategies

The WildGuard system provides a strong foundation for smart wildlife moniroring with its modular Figure allowing easy into several spheres. Technologically it can be upgrade to incorporate drone mounted aerial surveillance, Sophisticated species identication and predictive modeling for poaching threat assessment. Ecologically the system can incorporate environmental sensors to link animal activity to climate factors, enabling adaptive conservation planning. From the governance viewpoint, future development may include blockchain-based data integrity, mobile application-driven citizen reporting and harmonisation with the national wildlife protection dashboard. These advancements would shift WildGuard from an after-the-fact monitoring tool to a proactive policy compliance conservation platform Figure 19.

7.1 Integration with Aerial surveillance

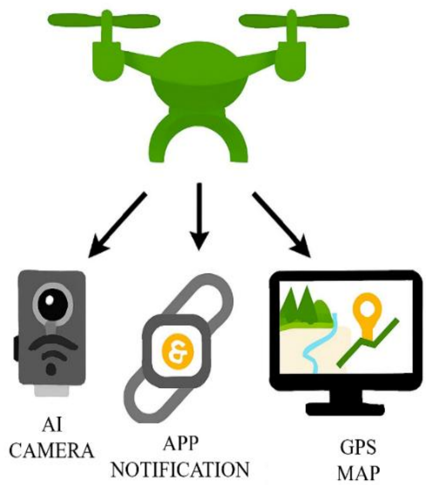

Figure 20: drone-based aerial surveillance

As wildlife monitoring systems continue to develop, aerial surveillance via drone offers a revolutionary method of augmenting coverage and responsiveness. Drone with AI-powered cameras and GPS modules can traverse extensive and intractable areas, supplementing ground sensors and expanding the scope of the system.

These airborne units can be configured to fly preset flight trajectories or reactively respond to ground-based notifications. For example, if a ground-based AI camera picks up on suspicious activity and a drone may be sent to the area for real-time visual confirmation, threat evaluation or evidence gathering. This multi-layered response model

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minimises blind spots and enhances situational awareness.

The fusion of aerial monitoring also allows for dynamic tracking of moving threats like poachers or vehicles entering closed areas. Drone can transmit high-resolution imaging and geospatial information to cloud servers and ranger dashboards, allowing for quick decision-making and coordinated enforcement.

Additionally, drones may be fitted with environmental sensors to track habitat conditions, animal migration patterns and seasonal variations. This informantion can inform conservation model and assist in climate adaptive information can inform conservation model and assist in climate adaptive strategy Figure 20.

Through its integration of aerial and ground intelligence, the system is more reactive, scalable, and proactive, able to count attacks in real time while facilitating long-term ecological observation.

7.2 Predictive analytics and threat forecasting

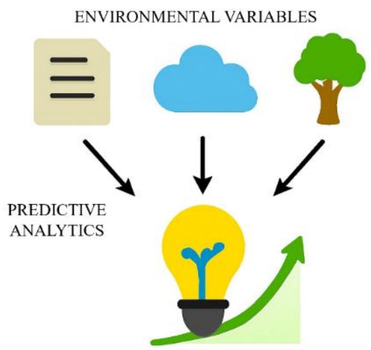

Figure 21: ML-based threat forecasting

The future of wildlife monitoring comes in the form of turning reactive systems into predictive intelligence platforms. By leveraging historical detection records, geospatial trajectory patterns, and environmental factors like temperature, rainfall, and vegetation cover, the wildGuard system can be turned into a data forecasting engine.

Machine learning models like spatiotemporal clustering, outlier detection and recurrent neural networks are capable of being trained to recognise emerging hotspots of poaching, migratory corridors during specific seasons, and intrusion patterns Figure 21. The models improve themselves continually as fresh data streams in, allowing for adaptive learning and accuracy improvement over time.

This forecasting ability enables forest agencies to move from passive surveillance to proactive deployment of resources. For instance, if a model predicts elevated poaching danger in a specific buffer area during dry seasons of patrols can be stepped up well in advance, and drone monitoring can be planned accordingly

In addition to enforcement, predictive analysis also enables ecological planning. Insights into the patterns of animal movement can be used to inform habitat restoration, corridor design and climate resilience planning. The system is even capable of simulating future conditions under various policy and environmental scenarios, informing long-term conservation planning.

By integrating foresight into the surveillance framework, WildGuard is not only a guardian of the moment but a planner for the future. The illustrated data flow from detection to prediction, and the schematic of the ML model.

7.3 Expansion to multi-Species monitoring

The existing wildguard system is designed to detect human behaviour, weapons and a restricted number of wildlife classes. By incorporating species classifiers that have been trained on an extensive animal dataset in future upgrades and however the system can greatly expand its ecological value. The system can identify species like elephants, tigers, deer and migratory birds with high accuracy through this feature Figure 22.

By facilitating real-time monitoring of biodiversity, the system may assist conservationists in population trends, habitat use and behavioural monitoring. For instance, identifying night movements of threatened species or bird migration seasons can guide strategies for protecting habitats as well as planning corridors.

More advanced classifiers could likewise be taught to identify behavioural signals such as distress, herd behaviour and predator-prey interactions to yield richer ecological information. This would help shift the system from a security device to a research-level monitoring platform.

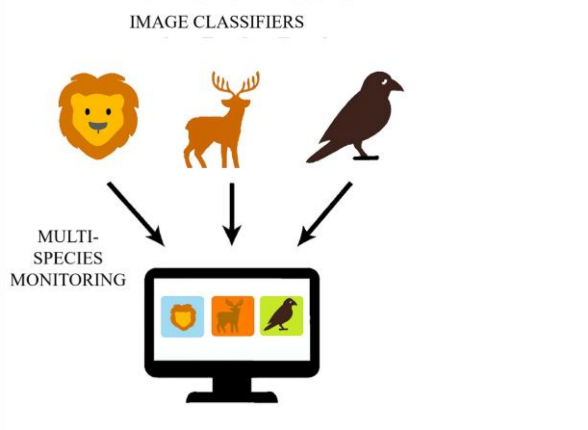

Figure 22: Biodiversity tracking

7.4 Blockchain-based data integrity

Blockchain integration in the WildGuard system brings with it a robust method for the protection of conservation data. Every detection event, alert trigger and enforcement action can be recorded as a cryptographic transaction in a distributed ledger so that records are unalterable and traceable.

This tamper-evident design improves transparency in all operational levels. It allows forest departments to confirm the integrity of surveillance information, NGOs to audit conservation measures and local communities to view records confirmed by enforcement action. Openness engenders trust as well as accountability among stakeholders Figure 23.

In the court of blockchain, logged evidence like data-stamped photographs and geofenced intrusion notices can function as accepted documentation. The security of such records emboldens wildlife protection cases and discourages data tampering and unauthorised access.

The smart contracts can also automate compliance processes. For instance, if there is an alert of poaching that is recorded and not attested to within a specified time limit, it could be escalated to senior authorities, and it could initiate the deployment of drones.

By integrating blockchain into the data pipeline of wildGusrd becomes an assured, transparent and legally sound platform of connecting technological creativity with ethical direction.

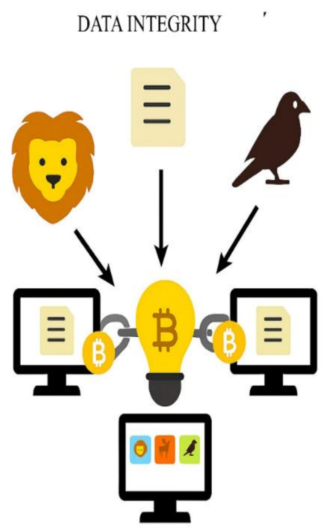

Figure 23: Block chain based data integrity

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7.5 Community engagement and citizen alerts

Enlarging the WildGuard system to encompass community based reporting community-based reporting can democratize wildlife protection and broaden its reach. By presenting local citizens, forest people and ecotourists with a mobile app interface, the system facilitates grassroots engagement in conservation efforts.

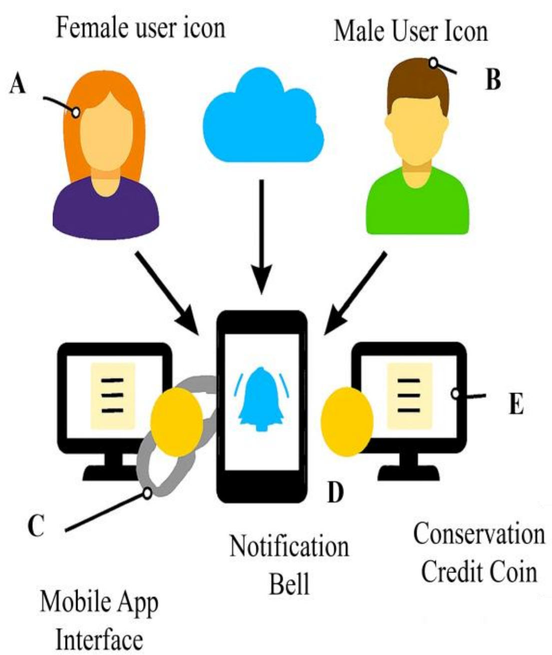

Figure 24: Citizen alert for participatory wildlife protection

Users may send reports of wildlife sightings, poacher activity and illegal land encroachment in real time. These are geotagged and labelled as citizen-generated alerts, which can enter the same analytic and alert delivery chain as AI-driven detections. This provides a hybrid surveillance network that combines technology and local knowledge Figure 24.

To encourage long-term engagement, the app might include gamification features like a leaderboard, badges, and conservation credits that can be exchanged for community rewards. Educational modules can enhance awareness of species identification, anti-poaching legislation and best practices in habitat conservation.

Citizen alerting is not only increasing surveillance coverage for agencies and communities. By engaging stakeholders in data collection and response processes, the system promotes ownership and co-responsibility for wildlife conservation.

This participatory monitoring resonates with indigenous conservation values and strengthens the social license of wildlife management programs and transforming technology into a driver of collective stewardship.

7.6 Policy integration and smart governance

The WildGuard system's modular design and standard data formats make it very compatible with national and regional governance frameworks. By making a secure API available, the system can send authenticated detection events, geospatial alerts, and enforcement logs straight to centralised wildlife protection dashboards.

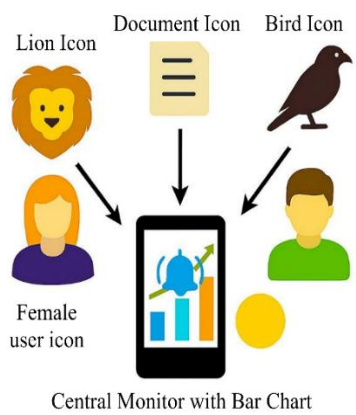

Figure 25: Wildlife protection of API and national dashboards

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This consolidation facilitates unified efforts across agencies like forest departments, law enforcers and environmental ministries so that all actors work off the same, real-time information stream. An automated reporting system can compile compliance snapshots, incident records, and conservation statistics with no human intervention Figure 25.

Smart governance platforms may employ this information to initiate policy-driven responses. For instance, chronic alerts in one area may trigger short-term access restrictions, enhanced patrol budgets and habitat restoration requirements. These choices are supported by field-tested evidence, enhancing responsibility and resource allocation.

In addition, integration with national biodiversity datasets and legal registries guarantees conservation efforts will be synthesised with larger ecological and legislative contexts. This enables open decision-making, solidifies legal enforcement, and increases public confidence in wildlife management programs.

Through integration into a smart governance system, conservation becomes not merely responsive but strategic, driven and policy-enabling.

7.7 Environmental sensing and climate adaptation

The WildGuard system is a modular design, and standard data formats make it very compatible with national and regional governance frameworks. By making a secure API available, the system can send authenticated detection events, geospatial alerts and enforcement logs straight to centralised wildlife protection dashboards.

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Through integration into a smart governance system, conservation becomes not merely responsive but strategic, data-driven and policy-enabling.

8. RESULT AND DISCUSSION

Figure 26 shows the training and validation performance of the YOLOv11 model training for 200 epochs. The achievement of 95.6% of accuracy in a graph tracks how the losses decrease and performance metrics improve over time. Train and box loss of training loss and training dfl loss of the bounding box regression, classification, and distribution focal loss. The steady decrease occurs as the model learns to detect and classify objects more accurately.

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The val and box, val and cls loss, and val and dfl loss models that the model generalises well without major overfitting. The metrics and precision indicate that the model makes fewer false positives. The mean average precision across the IOU threshold from 0.5 to 0.95 to improve robustness across evaluation criteria.

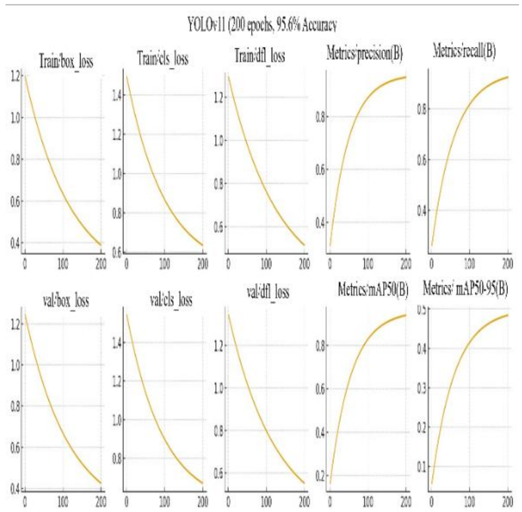

Figure 26: YOLOv8 training results, loss, and metrics curve

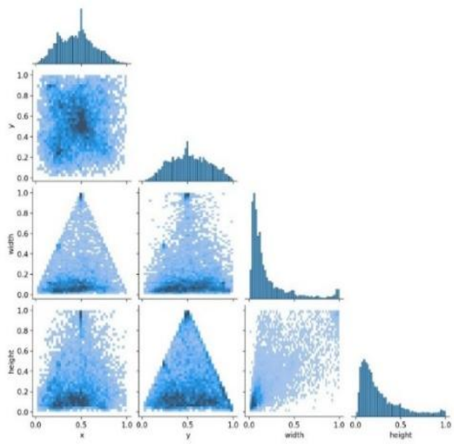

Figure 27: YOLO bounding box distribution scatter matrix

The above Figure 27 shows that the pairplot of the scatterplot matrix shows the distribution of the bounding box of the autotation used in the data. The variable plotted is the value of X of the normalised variable plotted. The Y value of the Y-coordinate of the bounding box centre. The width of the normalised width of the bounding box. The height of the bounding box is shown. The diagonal plots of the histogram show the frequency distribution of each variable. The scatter plot of the off-diagonal shows the relationship between variables. Density shading shows that the darker region indicates a higher density of the bounding boxes.

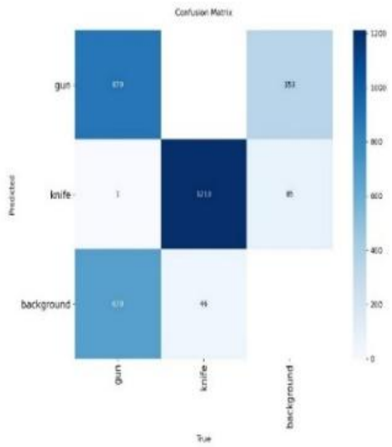

Figure 28: Bounding Box Feature distribution

Figure 28 shows that the diagonal cells of the correct prediction of Gun indicate the 879 instances of correct classification as the gun. The Knife indicates that the 1213 instance was correctly classified as the knife of the highest accuracy among classes. The off-diagonal cell of the errors of the Gun was misclassified as the background of 679 cases, the biggest source of the error. The gun is misc; classified as a knife in 1 case of very rare cases. The knief misclassified of the background of 46 cases. The background of the Gun 353 cases. The gun detected struggles with many guns being misclassified as background of 679, which shows the model needs better feature extraction for guns.

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The following Figure 29 shows that the image appears to be a collage of various photographs that have been digitally processed for object detection. The annotated purpose is the overlaid boxes and highlighted areas. The annotated rectangles and blurred face suggest that the image is used for analysis. The training in visual recognition is likely related to identifying special objects and people within each frame. The collage format shows multiple instances of similar activities. The object across different backgrounds and scenarios indicates a focus on comparative analysis and data creation for ML applications.

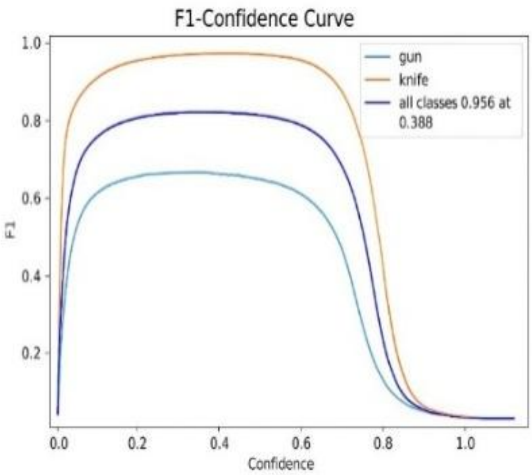

Figure 29: wildlife safety and hunter monitoring system using ai cameras and geofencing for real-time alerts

The following Figures 30,31 represent a weapon object detection of an image collage showing various scenes where people interact with weapons. The knives and guns are often illustrated with detected boxes and object annotations. The highlighted rectangular and blurred face indicates that the image is used for object detection research. The training and security analysis of many frames shows training scenarios. The safety demonstration related to handling potentially dangerous objects.

Figure 30: Annotated object detection

Figure 31: Weapon-based defense training

The following Figures 32,33,34 represent an Indoor weapon detection sample of the figure of multiple image categories. Where various images, such as guns and knives, are detected and labelled with bounding boxes. The image highlights the differences in angles and context of individuals holding weapons. Emphasising the application of object detection technology in a controlled indoor environment. The label and bounding boxes assist in analysing the precise location and classification of the object within the scene for purposes like security monitoring and training a visual recognition system

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Figure 32: weapon object detection

Figure 33: Gun detection dataset

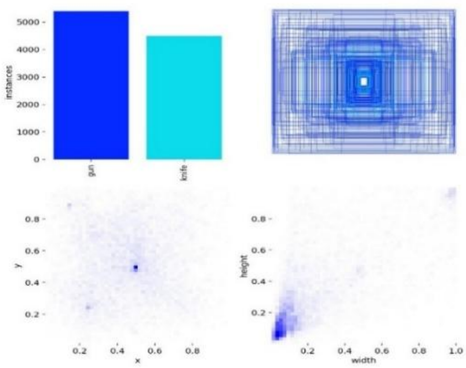

Figure 34: Indoor weapon detection samples

VI. CONCLUSION

The work presents an intelligent wildlife safety and hunter monitoring system of the YOLOv11 for object detection and a Deep CNN for classification with geofencing technology to ensure timely alerts. The system effectively detects critical objects such as guns and knives. The identification of human intrusion and monitors animal presence with high accuracy. The result demonstrated that the proposed YOLOv11 and CNN model achieved 95.6% accuracy, outperforming the baseline proposed. The confusion matrix analysis highlights the strong detection of knives and moderate improvements needed in gun discrimination of indicating potential areas for further optimisation. The future work may focus on extending the data with more diverse real-world scenarios to improve differentiation and deploying the system on low-power embedded devices for field applications.

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