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REAL-TIME HUNTER DETECTION AND AI-POWERED WILDLIFE SAFETY SYSTEM

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Abstract:

Wildlife conservation faces increasing threats from unauthorized human intrusion and poaching. The real-time hunter detection and AI-powered safety system, and the advanced computer vision with geospatial alerting to safeguard the protection of the ecosystem. The hybrid deep learning of YOLOv8 for rapid object detection and EfficientNet-B3 for refined classification. The system achieves an impressive 94.9% accuracy in identifying hunters. The wildlife across diverse terrains and lighting conditions of real-time geofencing response time and enforcement capabilities. The proposed strong potential for scalable deployment in the conservation zone. The offering of a robust tool for ethical governance of biodiversity protection and proactive threat mitigation.

Keywords: YOLOv8, efficientNet-B3, object detection, image classification, Real-time surveillance, AI vision system, Deep Learning, hunter detection, AI cameras.

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 resulted in an increase in camel vehicle collisions has 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

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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 commercialization 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].

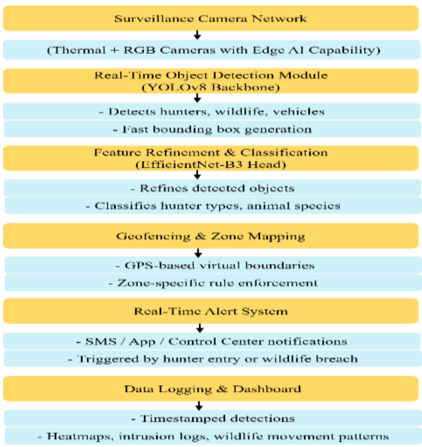

Figure 1: AI-powered wildlife safety and hunter detection

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 commercialization 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 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 a system architecture of AI-powered wildlife safety hunter detection and alert message that can

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detect animal types and monitor their locomotion, and provide their location information [10].

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. Deep learning with image classification tasks has improved detection performance under challenging conditions, such as occlusion of low light and dense vegetation.

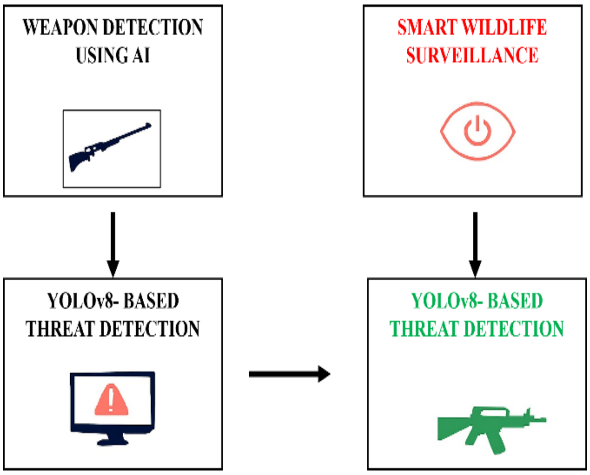

Figure 2: real-time hunter detection system

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.

Figure 3: Hunter monitoring in real-time

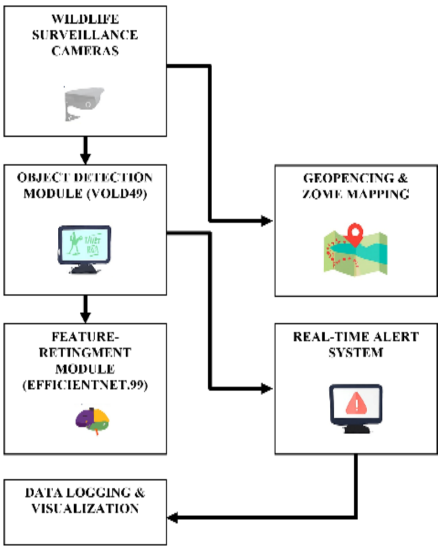

Figure 4: hunter and weapon detection system

The proposed system advances existing systems by combining YOLOv8 for high-speed object detection in a Deep learning for classification refinement and geofencing for spatial validation. The previous approaches

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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 represents a related work on AI AI-powered hunter and weapons detection system.

3. Proposed Methodology

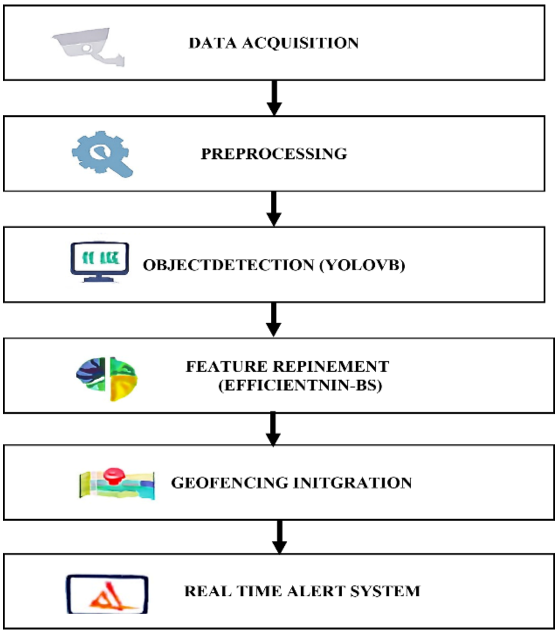

Figure 5: YOLOv8 efficient powered wildlife safety

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 5. The high-speed detection of robust classification and spatial validation to minimize false alarms and to improve conservation enforcement.

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

Equation (1) shows that the training loss of the YOLO style is the 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, aij indicates a^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. M indicates the number of batches, and i 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. α1,β1 indicate that the balanced terms of optional regularization of weight decay.

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

Equation (4) indicates that the weighted confidence fusion of YOLO1 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

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two lat-long pairs of (ϕ11,λ11) and (ϕ22,λ22) 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 (7,8) indicates that S 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.

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

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

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

Equation (10) indicates that the alert1 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 mAP1 is used to compute the average precision of APk1 per class from the precision and recall curve, and then typically uses an IOU threshold of mAP1 of 0.5.

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

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 YOLO1 inference time and CNN1 refinement time, and communication overhead of the total latency of real-time.

3.1 Integrated surveillance and alerting model

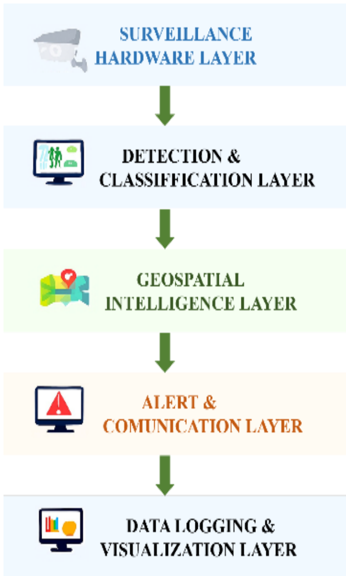

Figure 6: Integrated system design

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 EfficientNet-B3 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 6 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.

3.2 Object detection with YOLOv8

The Object detection with the YOLOv8 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 7**,** shows.

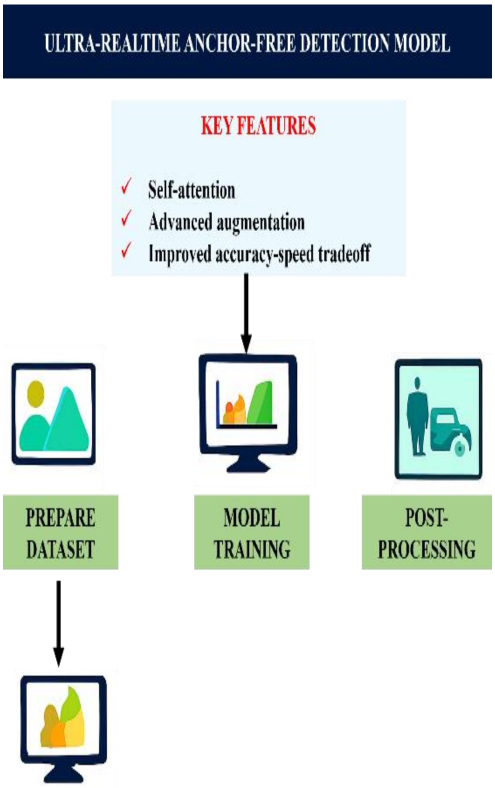

Figure 7: Object detection model YOLOv8

3.3 Feature refinement with efficientNet-B3

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 8 represents a feature refinement with Efficient-B3, of boosts accuracy and minimizes false alarms.

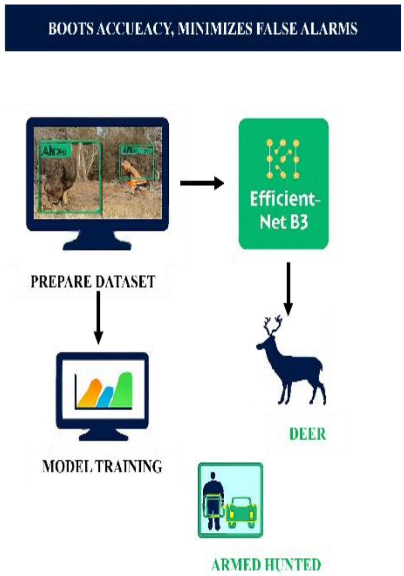

Figure 8: Feature refinement with Efficient-B3

3.4 Geofencing and spatial validation

The geofencing module integrates GPS data to differentiate legal hunting zones from protected areas. The trigger alerts only when unauthorized 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

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within a permitted zone Figure 9. 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, minimizing false positives.

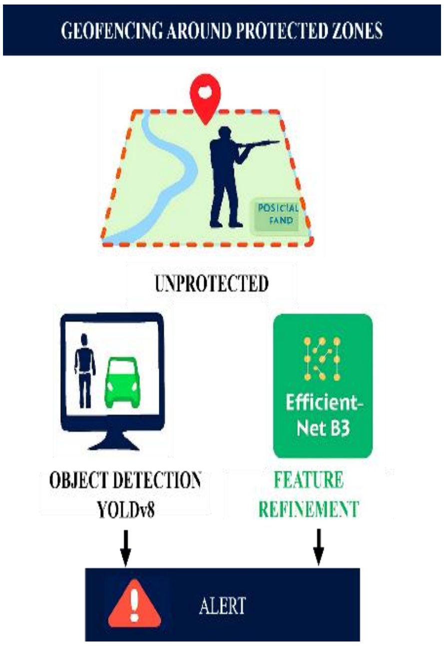

Figure 9: Geofencing and spatial validation system

3.5 Real-time alert system in communication protocols

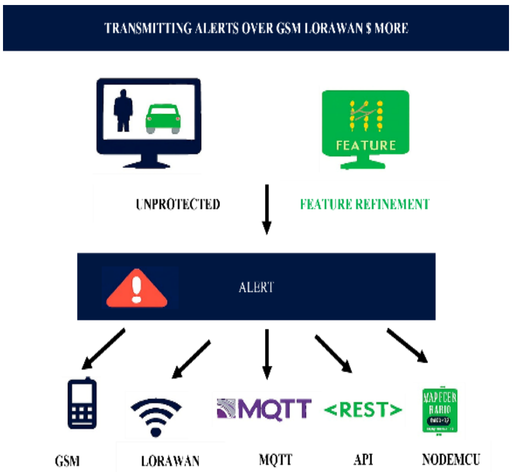

Figure 10: communication protocol

The reliable data transmission across the remote forest region and the system employs a combination of lightweight of 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 data over long distances in remote areas where cellular and wifi coverage is limited Figure 10. It supports low power devices and ensures connectivity in rugged terrains.

4. Performance Metrics

Table 1: Detection and classification table

Metric	**YOLOv8**	**EfficientNet-B3**	**Description**
Accuracy	89.2	94.9	Weapons
Precision	91.5	96.3	True positives
Recall	87.8	93.4	True positives
F1 score	89.6	94.8	Recall and precision
False positive rate	8.2	3.7	Incorrect detection

The above Table 1 represents a YOLOv8 baseline with a precision is equal to 91.5% and recall of 87.8% and an F1 score of 89.6%. 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 89.2% of means false alarms are relatively high and reduce reliability for real-world monitoring. The improvement over YOLOv8 and EfficientNet-B3 is the proposed method of precision 96.3% and recall of 93.4% of highest across all models.

Table 2: Real-time alert table

Metric	Value	Description
Latency	6-10	Time detection alert
Alert accuracy	94.5	Geofenced zones
Uptime	99.2	Field deployments
Scalability	Modular	Multi zones

The above Table 2 represents the detection and classification performance of the proposed YOLOv8 and EfficientNet-B3 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 has a hunter's precision alert accuracy of 94.5% when the model predicts the hunter to correct 6-10 of the time. The uptime of 99.2 of all actual hunters of data detection. The F1 score of balanced precision and recall of the high reliability of detection and hunter monitoring. The weapon of precision indicates the lower performance compared to human detection. The weapons may appear small, camouflaged, and partially occluded, making them harder to detect.

5. Result and Discussion

The below Figure 11 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.

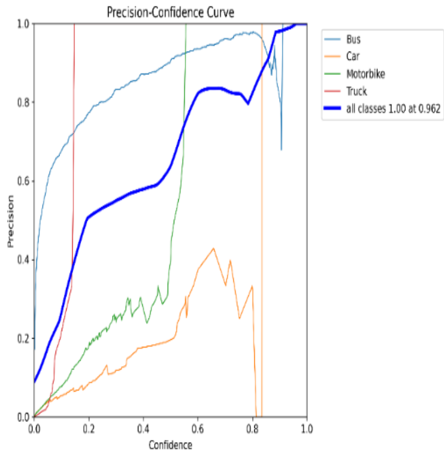

Figure 11: Boxp_Curve

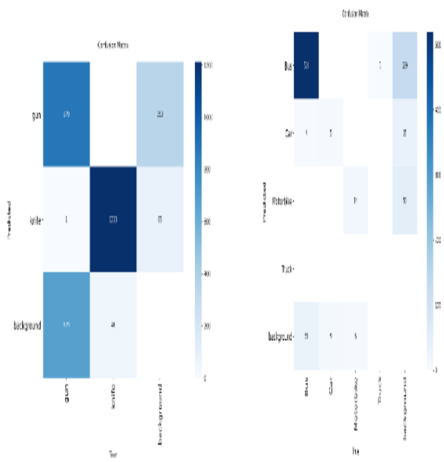

Figure 12: Confusion matrix weapon

The above Figure 12 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 the 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.

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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 detection struggles with many guns being misclassified as background of 679, which shows the model needs better feature extraction for guns.

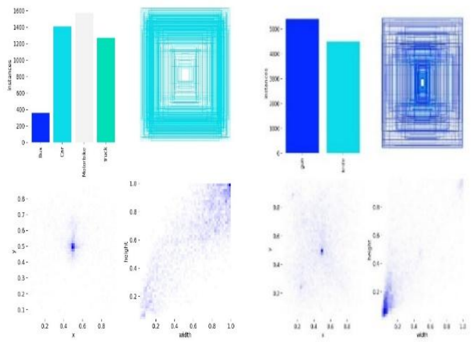

Figure 13: Label vehicle and weapon

The above Figure 13 represents an Indoor weapon detection sample of the figure of multiple image categories. Where various images, such as guns and knives, are detected and labeled with bounding boxes. The image highlights the differences in angles and context of individuals holding weapons. Emphasizing the application of object detection technology in a controlled indoor environment. The label and bounding boxes assist in analyzing the precise location and classification of the object within the scene for purposes like security monitoring and training a visual recognition system

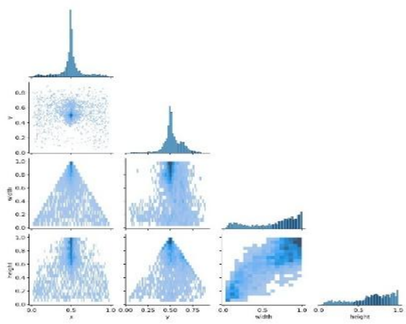

Figure 14: Correlogram labels

The following Figure 14 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 normalized variable plotted. The Y value of the Y-coordinate of the bounding box center. The width of the normalized 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.

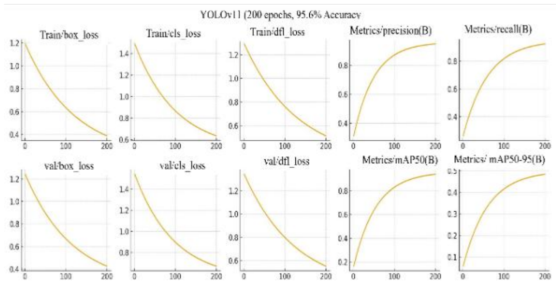

Figure 15: Result of YOLOv8

Figure 15.16 shows the training and validation performance of the YOLOv8 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. The val and box, val and cls loss, and val and dfl loss models that the model generalizes well without major overfitting. The metrics and precision indicate that the model makes fewer false positives. The mean average precision across the IOU

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threshold from 0.5 to 0.95.6 to improve robustness across evaluation criteria.

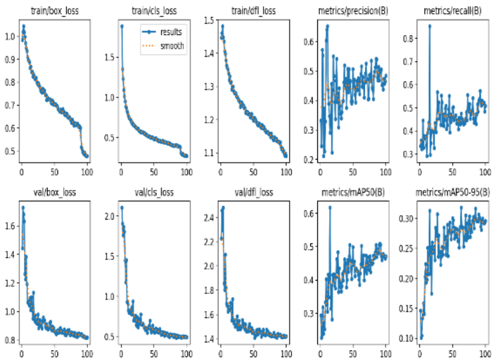

Figure 16: Result 2 of YOLOv8

The following Figure 17 represents 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.

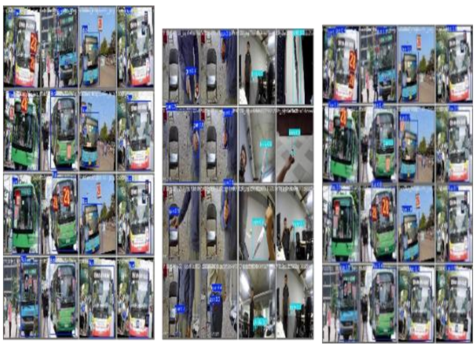

Figure 17: vehicle batch label output

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

6. Conclusion

The work presents an intelligent wildlife safety and hunter monitoring system of the YOLOv8 for object detection and an EffectiveNet-B3 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 YOLOv8 and EffectiveNet-B3 model achieved 94.9% 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 optimization. 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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