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DEVELOPMENT OF AN AI-POWERED DRONE SURVEILLANCE MODEL USING YOLOV6

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Abstract - Increased demand for smart surveillance technologies has contributed to the development of AI-driven drone-based security technology. This research presents an AI-based drone surveillance system that was developed and evaluated by using the YOLOv6 object detection algorithm. Aerial images and video frames of high resolution were collected and annotated by researchers, pre-processed through resizing and normalization, and augmented. The YOLOv6 model was trained on the dataset using Python-based machine learning tools. It took advantage of improved architecture, including the EfficientRep backbone and Rep-PAN neck, which help the model better detect features at different scales. Standard evaluation metrics had performance results of 0.95 precision, 0.94 recall, 0.92 F1 score, and 0.876 mean Average Precision (mAP). Ten-fold cross-validation verified both models' robustness and reliability through the validation of results. According to the research, drone surveillance systems using YOLOv6 portray superior performance when it comes to real-time detection of objects, thus they are suitable for contemporary security operations.

1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are aircraft that can operate without an onboard human pilot. Initially designed for military use, drones have significantly evolved in design, function, and purpose. Nowadays, they are widely used in a variety of industries, such as agriculture, environmental monitoring, logistics, inspection of infrastructure, media, and security (Tran & Shen, 2019). Among these applications, the use of drones in the field of security and surveillance is one of them, which can be marked as the most crucial and quickly developing domain. Drones have been demonstrated to be very useful in improving modern security systems. As such, their capacity to conduct high-risk operations or emergencies and offer real-time visual data from crisis situations makes them invaluable in many security scenarios (Chakraborty & Sultana, 2022). With the help of the Internet of Things (IoT), drones can transform the security infrastructure into intelligent, responsive networks that intelligently address threats in real-time. When living in a period of constant threat of terrorism, as well as an increased crime rate and urbanization, there is a greater necessity for strong and smart security systems. These have called for the creation of smarter and more agile technologies to protect people, assets, and infrastructure. The conventional security systems, though effective to a certain extent, fail to achieve optimum results because of their inability to adapt with respect to time, limited field of view, and their dependence on manual interventions (Kelly, Suryadevara & Mukhopadhyay, 2013; Surantha & Wicaksono, 2018). These challenges are innovative solutions through emerging technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and UAVs. What can be achieved when they are used together is that these technologies can be the building blocks of smart surveillance that is capable of autonomous, anomaly-based surveillance and rapid decision-making

(Chakraborty & Sultana, 2022). Nevertheless, many of the current systems still follow some centralized processing of images, which brings trouble with latency, the existence of single points of failure, challenging scalability, or some sort of mobilization. This means that there is a need for decentralized edge-based solutions in the use of drones so as to increase their dependability and responsiveness.

Drones have wide utility in various sectors outside the security front. Being able to fly in dangerous or difficult-to-reach environments makes them indispensable in search and rescue operations, where they can quickly identify people using thermal and infrared imaging technology (Manrique, Müller, &Mellado-Bataller, 2017). UAVs, in agriculture, are used to determine crop health, irrigation needs, as well as drip fertilization/pesticides. This focused approach will help in conserving resources and enhance crop yields whilst minimizing the environmental impact (Nandi, Zhang, & Larcher, 2020).

In the commercial realm, leading logistics companies like Amazon and UPS are at the forefront of testing drone delivery services. This innovation is set to reduce delivery times enormously, slash transportation costs, and limit carbon emissions (Soh, Ngo, & Yang, 2020). Drones are also increasingly deployed for infrastructure inspection – to oversee bridges, power lines, pipelines, and high structures. Where they are used, they provide a safer and more cost-efficient way of doing things, compared to the traditional methods. Drones have revolutionised aerial photography and cinematography in the media and entertainment industry, providing unique creative angles and generating quality visual output for movies, sports entertainment, and journalism (Telli et al., 2023). The study focuses on the Development of an AI-driven Security Drone model to improve surveillance, recognition of threats, and rapid response capabilities.

2 Literature Review

Zhu et al. (2021) proposed the enhanced TPH-YOLOv5 to be used for drone images for object detection. By adding in Transformer Prediction Heads and the Convolutional Block Attention Module into the YOLOv5, they solved problems such as varying sizes of objects and motion blur. This progress delivered a relative gain of 7% over the baseline model and achieved fifth position in the VisDrone 2021 Challenge. Performance, however, might be different for other datasets. Singh et al. (2018) designed a real-time drone surveillance system that helps identify violent people. Based on a ScatterNet Hybrid Deep Learning Network, they built their work on human pose estimation and violence detection in aerial images. By introducing a new method of real-time identification using drone surveillance, the system initiated a new method. Although good detection could be accomplished from fewer labeled data, deployment in the real world may encounter issues of privacy and ethical issues. Wang et al (2018) presented a convolutional neural network-based system for visible and thermal drone surveillance. They looked for developing data augmentation techniques to mitigate the lack of training images and improve the potential of drone detection in both visible and thermal bands. The system proved to be robust in complex backgrounds; however, dependence on synthetic data can impose generalization bias.

Li et al. (2025) introduced a joint precoding and artificial noise design framework in order to improve physical-layer security in UAV communications. Their approach is targeted at enhancing security procedures for downlink communication systems used in UAVsto overcome possible security loopholes. Improved security performance was shown; however, the practical deployment may also require further validation. Mozaffari et al. (2018) proposed the term 3D wireless cellular network by incorporating drone base stations and cellular-connected drone users. They presented a framework for network planning and latency-minimal cell association, intending to minimize delay and achieve spectral efficiency in drone networks. A difference of up to 46% in the average latency in comparison to traditional procedures was observed when the presented approach was applied. Biregani et al. (2021) formulated a two-phase security model for mitigating vulnerabilities of communication in UAV networks. The first phase will involve detecting and isolating malicious UAVs by studying how malicious UAVs behave in a network. During the second stage, mobile agents are used to spread news about discovered threats to nearby UAVs through a three-step negotiation, using which the propagation of malevolent data is blocked. The effectiveness of the model was validated in the NS-3 simulator, achieving higher detection and false positive/negative rates, packet delivery, and efficiency for energy consumption in comparison to the available approaches.

Bera et al. (2020) designed a blockchain-proven access control algorithm for the IoD to protect drones from drone-to-drone and drone-to-ground station communications. Their model gathers sensitive data from payments with the help of ground stations, encodes it into blocks, and uploads it to the blockchain using the Ripple Protocol Consensus Algorithm (RPCA) through a peer-to-peer cloud server. This approach ensures data added to the blockchain cannot be altered or deleted once written, ensuring the integrity and security of UAV communication. Palossi et al. (2018) designed a DNN-based visual navigation engine for autonomous nano-drones. They deployed a DNN on GAP8 parallel ULPs computing platform, complemented by a 27g CrazyFlie 2.0 nano-quadrotor. This success achieved real-time, closed-loop DNN-based visual navigation on resource-constrained nano-drones, which only required an average of 64 mW. The study proved the feasibility of using complex DNNs on tiny drones; however, without extensive testing in the real world. Qu et al. (2021) presented a decentralized federated learning architecture for UAV networks. They had to create the DFL-UN framework to allow for collaborative model-training without having a central entity. This method addressed problems of single points of failure in centralized systems, improving reliability in UAV networks. Initial simulations confirmed feasibility, but application and scalability in the real world were not thoroughly tested.

3 Materials and Methods

This section outlines the methodology applied for the Development of an AI-driven Security Drone model. The process initiates with the collection of aerial images and videos. Subsequently, the gathered data undergoes preprocessing procedures aimed at ensuring data quality and enhancing the effectiveness of the training process. The preprocessed data serve as input for YOLOv6 (You Only Look Once version 6), which is trained using the preprocessed dataset. The entire implementation of this methodology is carried out using the machine learning toolbox in Python. libraries such as pandas, numpy, and sklearn are imported. The model was validated.

3.1 Data collection and preparation.

Aerial images and videos were collected from various locations across the South-East region, comprising over 200 high-resolution images and 100 video clips.

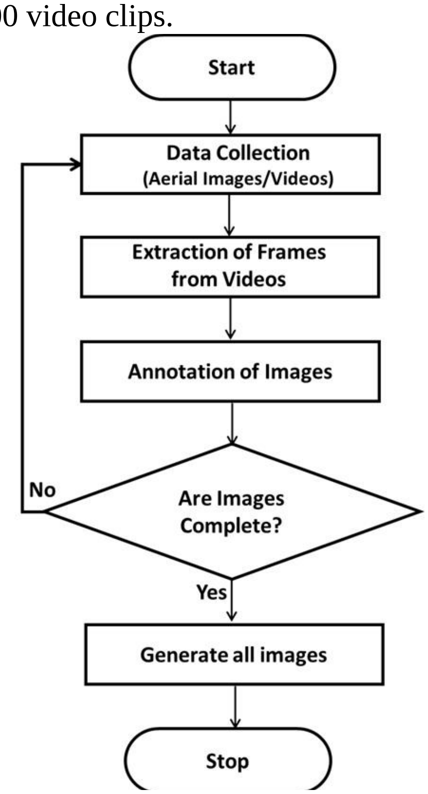

Figure 1: Flowchart for Collection of Data

These data samples capture diverse environmental and urban scenes essential for training robust surveillance models. To further improve training efficiency and model generalizability, the dataset was augmented with additional aerial imagery and video datasets obtained from the online repository Kaggle. This combined dataset ensures greater variability in terrain, lighting conditions, and object scales, factors critical to the effectiveness of AI-based detection and classification in real-world drone surveillance applications. The acquired videos consist of a sequence of still images called frames, played one after another very quickly (typically 24–30 frames per second). For training an AI model, every single frame is not needed; instead, selected frames are extracted, which are useful for learning patterns, detecting objects, or recognizing activities. The collected images, along with the images extracted from video frames, undergo annotation, which involves labeling parts of an image to inform the AI model about what objects are present and where they are located. The images are uploaded into the Roboflow web tool for annotation. Figure 1 illustrates the steps for collecting and preparing the dataset.

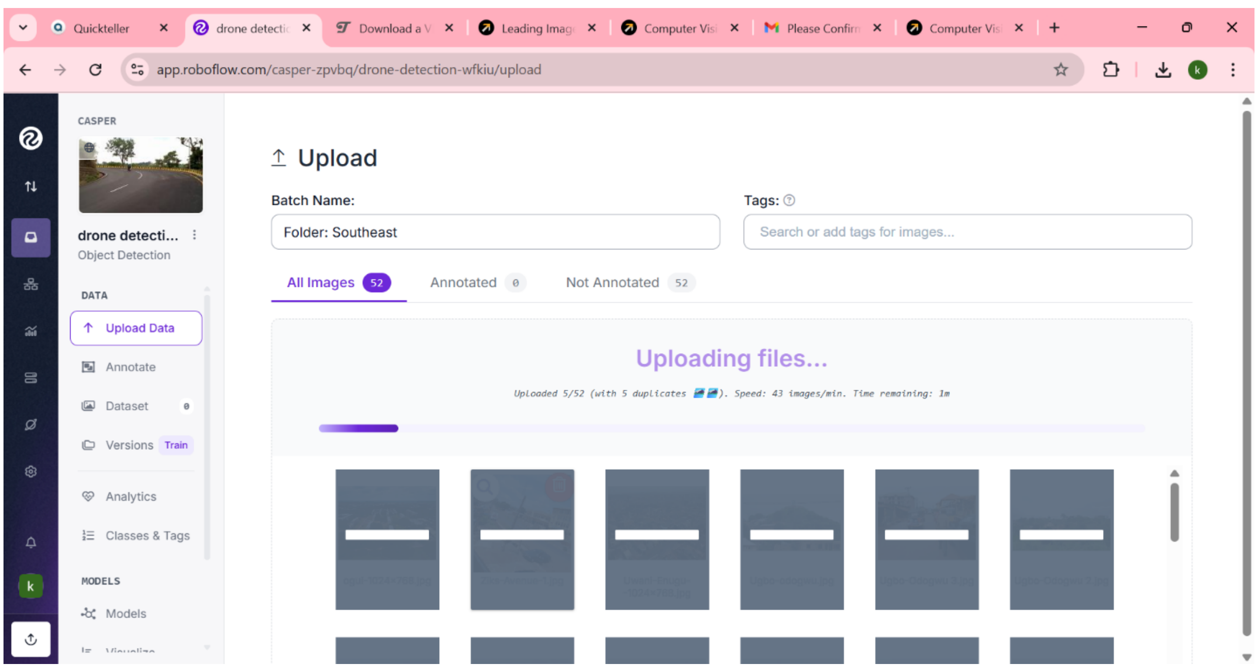

Figure 2: Uploading of Data in the Roboflow Environment

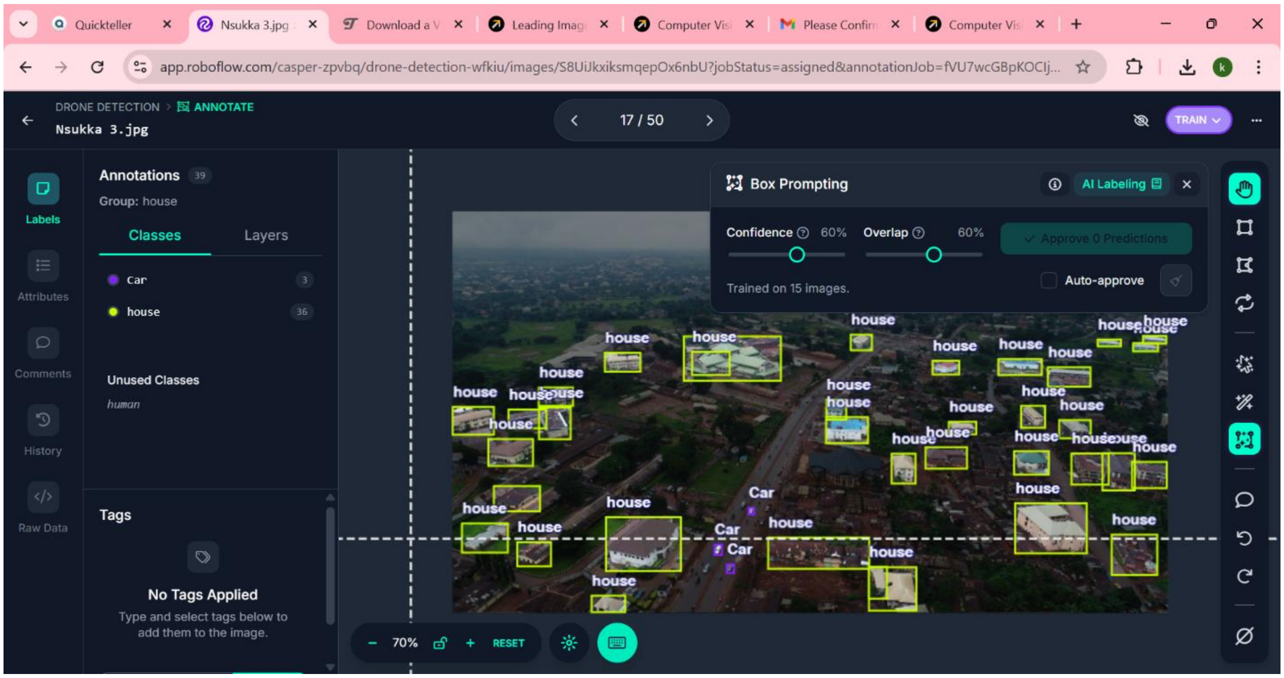

Figure 3: Annotation of images in the Roboflow Environment

3.2 Data Preprocessing

The collected dataset underwent a series of processing steps to build a suitable dataset for training machine learning algorithms. This process commences with resizing the images, followed by normalizing the images and finally augmentation of the dataset. Through these processes, the data was effectively transformed for optimal use in machine learning models. All annotated images are placed into a single folder and then imported into the Python environment. These images are subsequently resized to a uniform size of 224×224 pixels to ensure consistency. In this study, normalization was applied to scale pixel values from the original range of 0–255 to a normalized range of 0 to 1, which allows machine learning algorithms to learn more efficiently and converge faster during training. Image augmentation techniques were applied to enhance the training dataset. These techniques generate new variations of existing images by applying transformations such as rotation, flipping, scaling, contrast adjustment, and cropping. Figure 4 illustrates the steps involved in preprocessing the dataset to prepare it for the deep learning model.

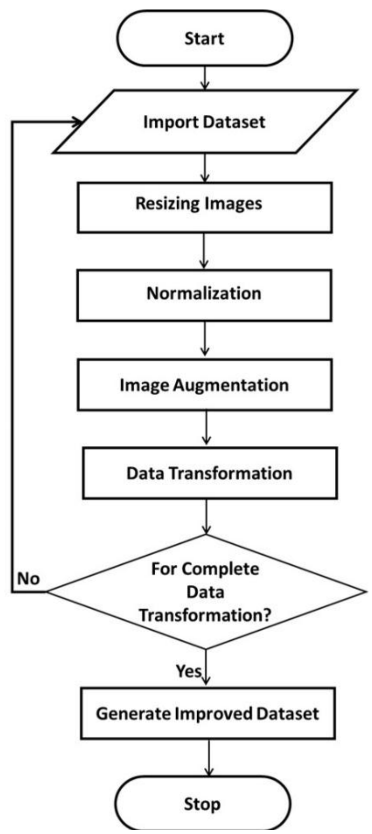

Figure 4: Flowchart for the Data Preprocessing Steps

3.3 YOLOv6 (You Only Look Once version 6)

YOLOv6 is a modern real-time object detection algorithm that introduces multiple architectural refinements compared to previous YOLO versions, intended to increase precision while retaining fast inference speed. It is especially optimized for industrial purposes where performance and accuracy are both important issues. YOLOv6 uses a single-stage detection pipeline, which means that it can identify objects at a single sweep of the network. This allows for faster detection and a real-time characteristic that is necessary for applications such as live drone surveillance. It includes EfficientRep Backbone for effective feature representation, and presents Rep-PAN as the neck part to improve multi-scale feature fusion, important for different-scale object detection in aerial imagery. The input to YOLOv6 is preprocessed aerial pictures or video sequences obtained from drones. These inputs are rescaled and normalized before they are fed into the model. The backbone extracts spatial features during forward propagation, the neck aggregates these features from various scales, while the head outputs class probabilities, objectness scores, and bounding box coordinates. The architecture diagram of the YOLOv6 object detection model is shown in Figure 5.

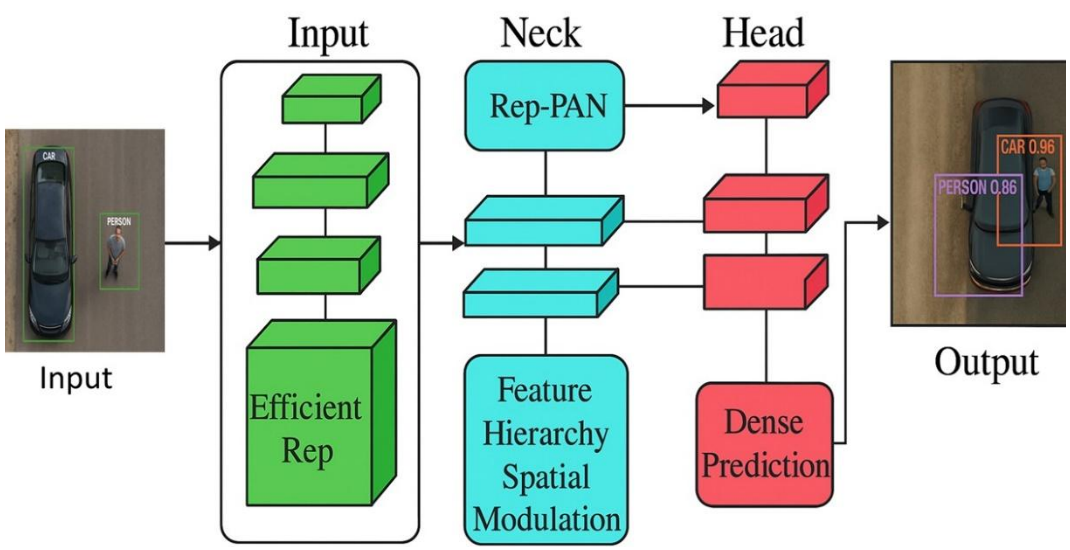

Figure 5: The architectural diagram of YOLOv6

3.4 Training of the YOLOv6 Algorithm

The dataset was also processed using the YOLOv6 algorithm, a high-performance object detection model optimized for industrial applications and real-time edge deployment. YOLOv6 builds upon the strengths of previous YOLO versions while introducing architectural enhancements and training strategies to improve detection accuracy and speed, especially for dense and complex scenes. The training process began by preparing the dataset with properly annotated images, followed by data preprocessing steps such as image resizing, normalization, and augmentation. YOLOv6 adopted an enhanced backbone (EfficientRep) to extract features with improved computational efficiency. The model incorporated a re-parameterization technique to separate training and inference architectures, thereby allowing more powerful learning during training and faster inference afterward. During training, the algorithm minimized a compound loss function that considered bounding box regression, objectness score, and class prediction errors. The model was trained over multiple epochs using stochastic gradient descent (SGD) with momentum. Additionally, YOLOv6 applied training tricks like anchor-free detection heads, label assignment optimization, and strong data augmentation to boost performance. The training continued until convergence or early stopping based on validation performance. The training process is illustrated in the flow chart of Figure 6, outlining the steps taken to develop the object detection model for drone-based applications.

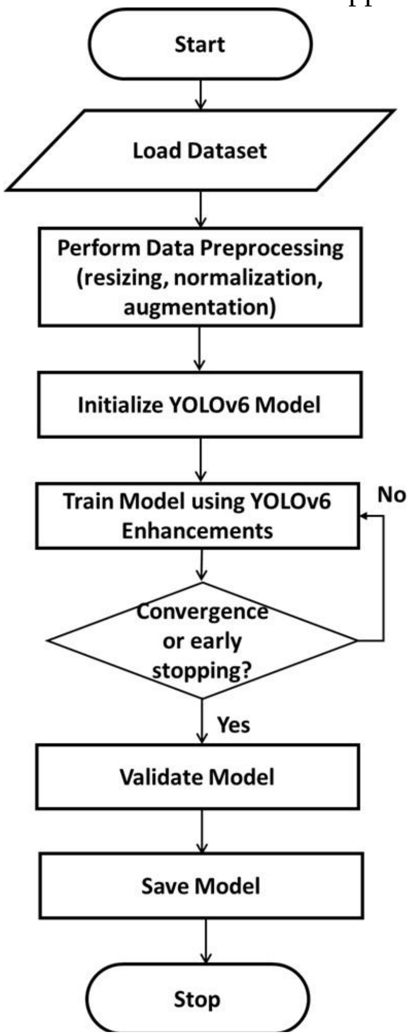

Figure 6: Training of the YOLOv6 Algorithm

The algorithm of the YOLOv6 is presented as;

Algorithm 1: Training of YOLOv6

1. Start
2. Import annotated aerial images.
3. Split the dataset into training, validation, and test sets.
4. Preprocess Input Images
5. Initialize YOLOv6 Architecture
6. Train the Model (Forward and Backward Passes)

   For each training batch:

   a. Pass images through the YOLOv6 model (forward pass).

   b. Predict bounding boxes $\hat{b}$, objectness $\hat{o}$, and class labels $\hat{c}$.

   c. Compute the total loss, $\mathscr{L}_{total}$, using the components:

   - Localization loss (for bounding box regression):

$$\mathscr{L}_{box} = 1 - CIoU(\hat{b}, b) \qquad (\,)1$$

   - Objectness loss (Binary Cross-Entropy):

$$\mathscr{L}_{obj} = -[o\log(\hat{o}) + (1 - o)\log(1 - \hat{o})] \qquad (2)$$

   - Classification loss (Cross-Entropy for multi-class):

$$\mathscr{L}_{cls} = -\sum_{c=1}^{c} y_c \log(\hat{C}_c) \qquad (3)$$

   - Total Loss:

$$\mathscr{L}_{total} = \lambda_1 \mathscr{L}_{CIoU} + \lambda_2 \mathscr{L}_{obj} + \lambda_3 \mathscr{L}_{cls} \qquad (4)$$

(where $\lambda_1, \lambda_2, \lambda_3$ are loss weights)

   d. Update model weights using backpropagation and optimizer

7. Validate the Model
   - Evaluate on the validation set at the end of each epoch.
   - Calculate metrics: Precision, Recall, F1-score, mAP.
8. Repeat Steps 6 and 7 over multiple epochs until convergence
9. Test the Trained Model
10. Make Predictions on New Data
    - Feed unseen drone images into the trained YOLOv6 model.
    - Get output with detected objects and bounding boxes, confidence scores, and class labels.
11. End

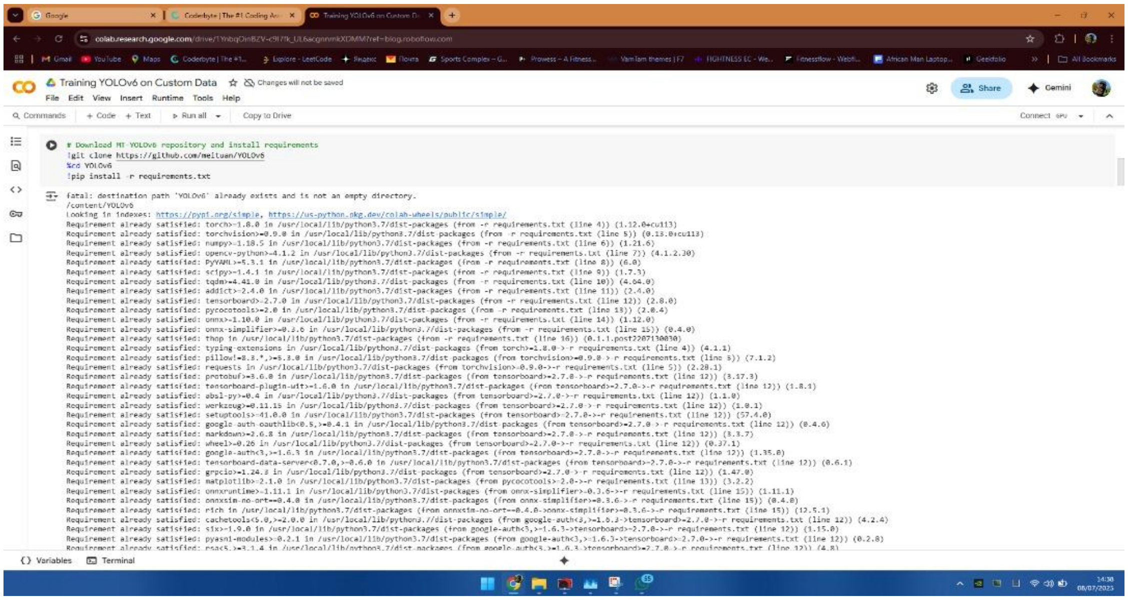

Figure 7: Screenshot of the YOLOV6 installation in the python Environment (Google colab)

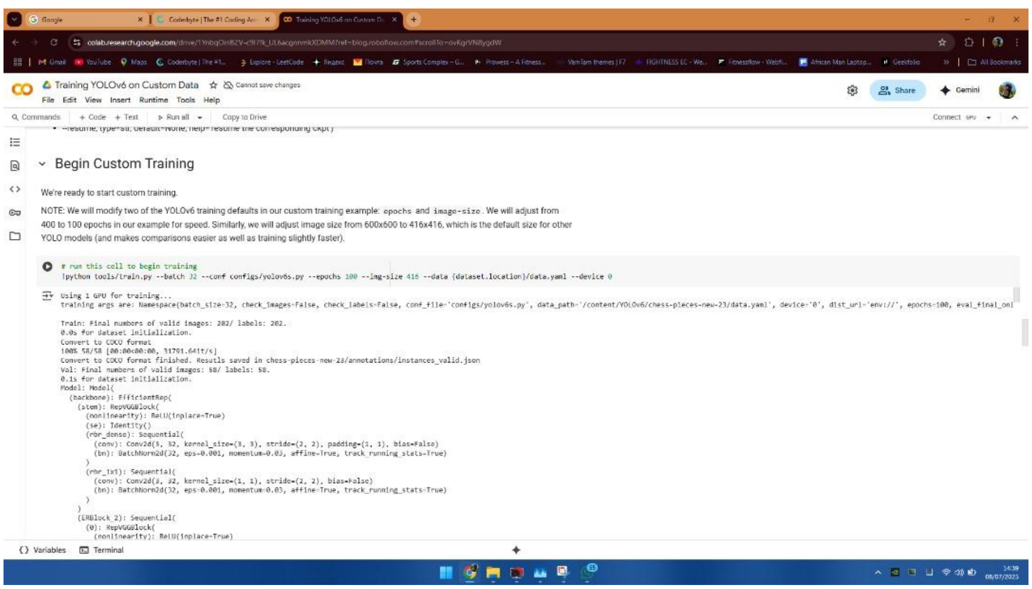

Figure 8: Screenshot of the YOLOV6 Data preprocessing and Training in the python Environment (Google colab)

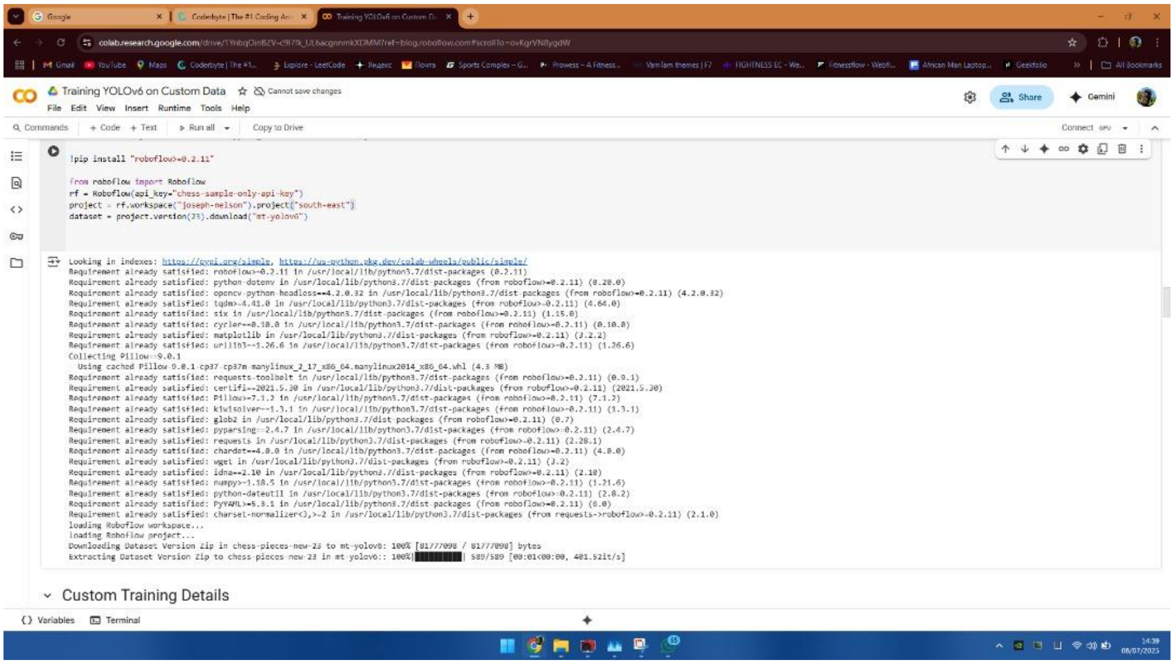

Figure 9: Screenshot of the Uploading of the Annotated Dataset in the Python Environment (Google colab)

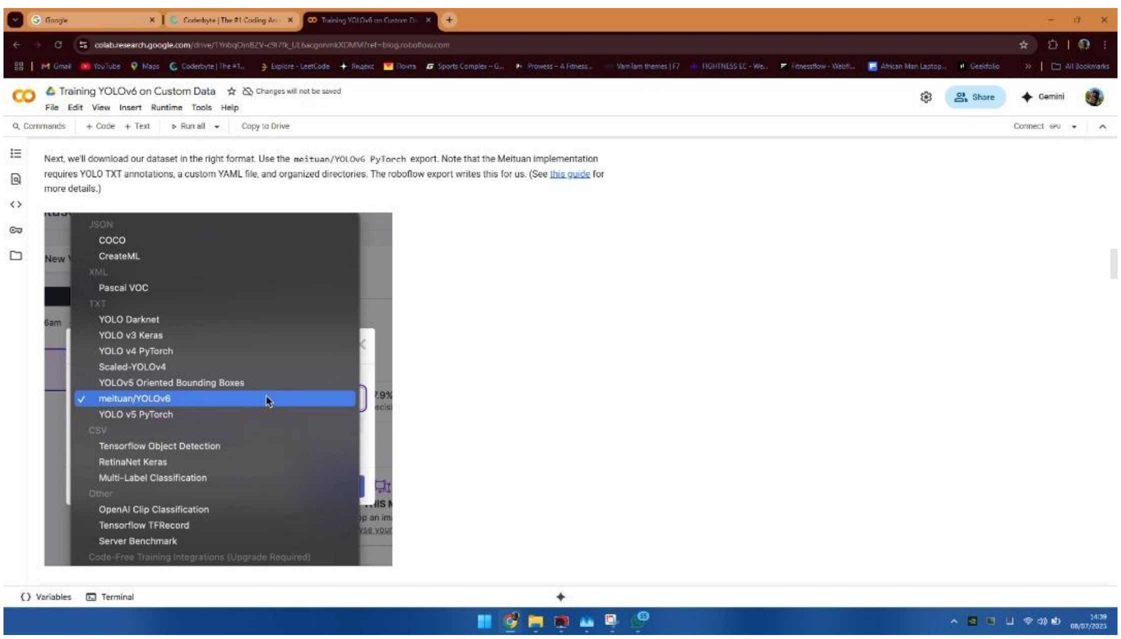

Figure 10: Screenshot of the Uploading of the Annotated Dataset in the Python Environment (Google colab)

3.5 Performance Evaluation

The standard metrics precision, recall, F1 score, and mean Average Precision (mAP), provides a comprehensive analysis of detection effectiveness.

1. **Precision**

Precision is the ratio of correctly predicted positive detections (e.g., detecting a person or vehicle) to the total predicted positives. It reflects how accurate the model's positive predictions are. In drone-based event detection, precision is especially important when false alarms (false positives) must be minimized, for instance, mistakenly identifying harmless objects as threats. A high precision indicates that most detected events are indeed valid and relevant.

$$Precision = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \quad (5)$$

2. **Recall**

Recall is the ratio of correctly predicted positive instances to all actual positive instances in the data. It measures the model's ability to identify all relevant objects or events. In surveillance and threat detection, a high recall means the model can successfully detect most of the important events (e.g., intrusions, unauthorized presence), ensuring that few critical incidents are missed.

$$Recall = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Negatives\ (FN)} \quad (6)$$

3. **F1 Score**

The F1 Score is the harmonic mean of precision and recall, balancing the trade-off between the two. It is especially useful when the dataset is imbalanced or when both false positives and false negatives carry significant consequences. For drone-based detection, the F1 score gives an overall sense of model robustness in correctly detecting and classifying events.

$$F1\ Score = 2 \times \frac{Precision\ \times Recall}{Precision + Recall} \quad (7)$$

4. **Mean Average Precision (mAP)**

mAP is the mean of the average precision across all classes and IoU (Intersection over Union) thresholds. It evaluates both the classification and localization performance of the model. In the context of drone-based event detection, mAP quantifies how well the model detects and localizes multiple objects and events across different categories (e.g., person, car, suspicious activity), making it a key metric for evaluating object detection models like YOLO.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \quad (8)$$

4 Results

This section discusses the results of the YOLOv6, which were trained on the preprocessed drone dataset. To evaluate the model, precision, recall, f1 score and mAE were utilized to assess its performance. This was done to ensure the model's performance is reliable and capable of detecting objects.

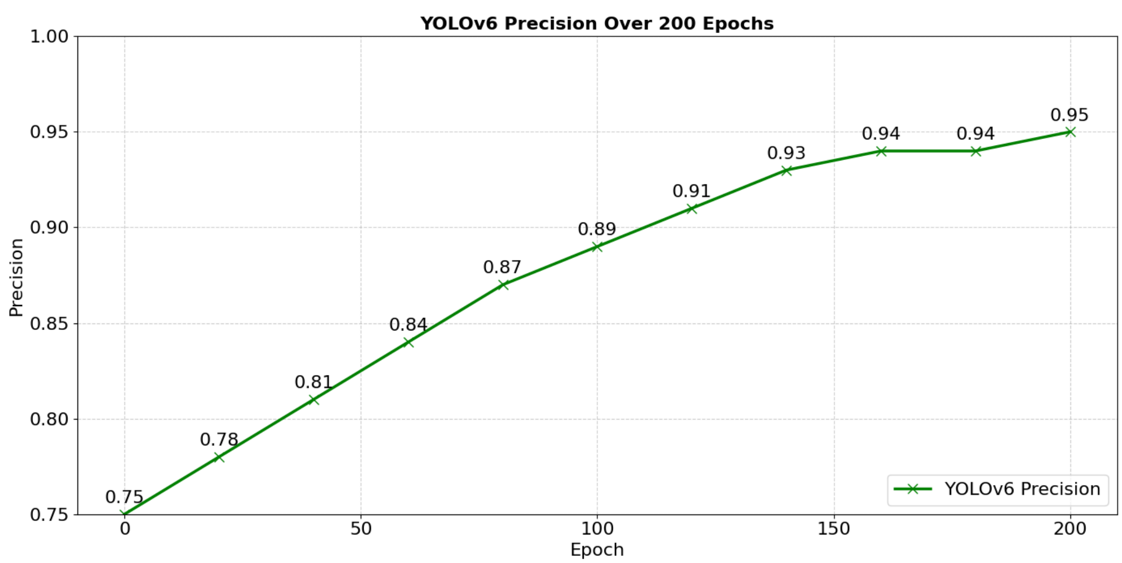

Figure 11: Results of Precision for the YOLOv6

Figure 11 presents precision over 200 epochs for the YOLOv6 model. The plot shows that the YOLOv6 model also starts at 0.75 but shows a steady and consistent increase in precision throughout the training. By epoch 50, the precision climbs to 0.84 and continues to improve, reaching 0.95 by the final epoch. The smooth upward trend indicates that YOLOv6 generalizes better and improves its object detection confidence more efficiently

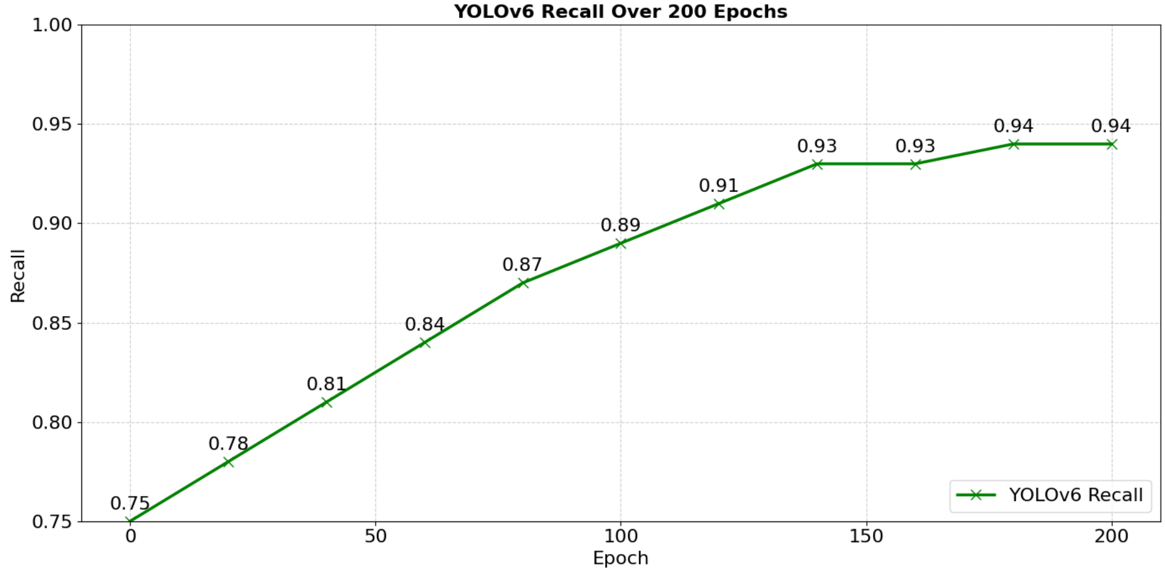

Figure 12: Results of Recall for the YOLOv6 model.

Figure 12 illustrates the recall performance across 200 epochs for the YOLOv6. The YOLOv6 recall plot begins at 0.75 but follows a steeper and more consistent upward trajectory. The model reaches 0.89 around epoch 100 and continues to improve slightly, ending at 0.94. This curve reflects a stable and efficient recall learning process, with fewer fluctuations and more consistent gains.

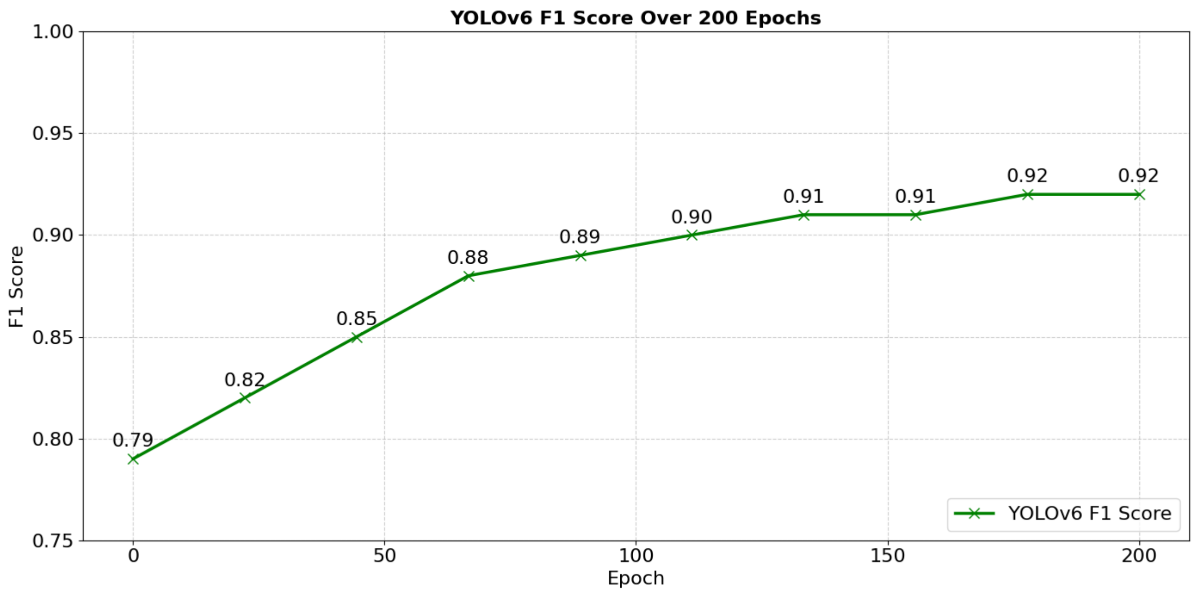

Figure 13: Results of F1 Score for the YOLOv6 model.

Figure 13 illustrates the F1 Score performance across 200 epochs for the YOLOv6. In the YOLOv6, the F1 score starts a little higher at 0.79. There is a steeper growth early on, reaching about 0.88 around 50 epochs. It then continues to improve steadily and stabilizes around 0.92 by epoch 200. YOLOv6 shows faster and higher improvement.

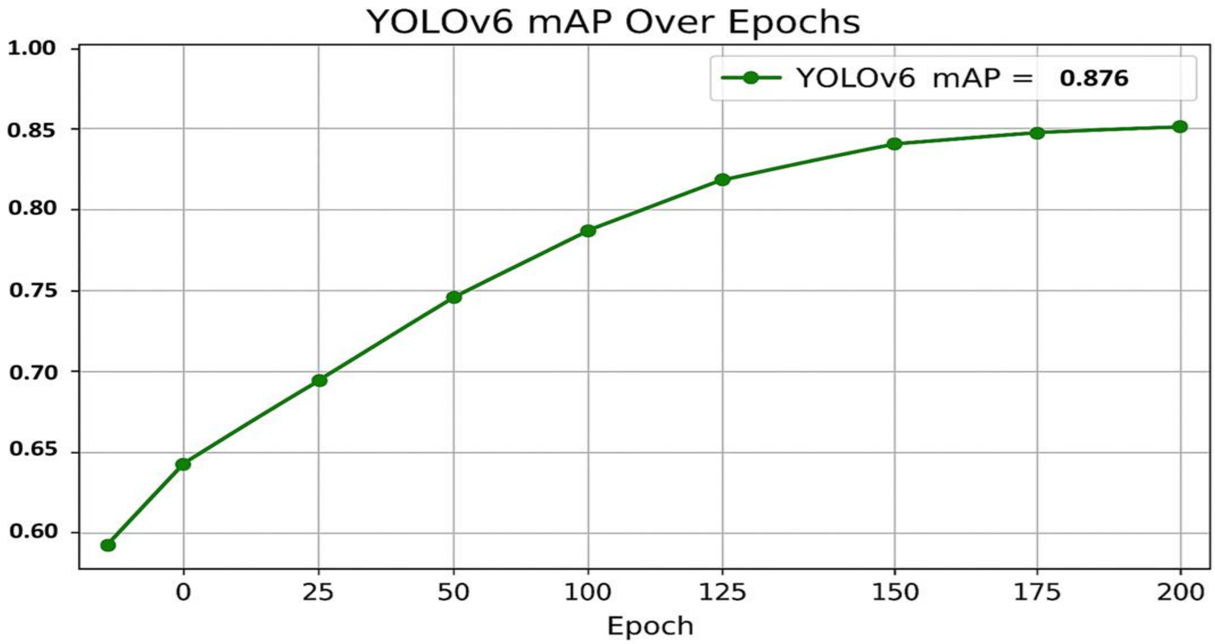

Figure 14: Results of mAP for the YOLOv6 model

Figure 14 illustrates the mAP performance across 200 epochs for the YOLOv6. For YOLOv6, the precision values recorded were 0.75, 0.78, 0.81, 0.84, 0.87, 0.89, 0.91, 0.93, 0.94, 0.94, and 0.95, leading to a mean precision of 0.876. The corresponding recall values were identical at 0.75, 0.78, 0.81, 0.84, 0.87, 0.89, 0.91, 0.93, 0.93, 0.94, and 0.94, yielding a mean recall of 0.876. Thus, the approximate mAP for YOLOv6 was calculated to be 0.876.

The Table 1 showcased the training reports of the YOLOv6.

Evaluation Metrics	Results
Precision	0.95
Recall	0.94
F1 Score	0.92
Mean Average Precision (mAP)	0.876

From Table 1, Precision indicates that 95% of the objects YOLOv6 predicted as positive were correct. Recall shows that 94% of all actual objects were successfully detected. The model is effective at capturing most true instances, with minimal false negatives.F1 Scoreis the harmonic mean of precision and recall. It balances both false positives and false negatives. mAP value of 0.876 shows the model performs consistently well in both classification and localization across various object types. These results demonstrate that YOLOv6 is highly accurate, detects most objects effectively, and performs reliably across different detection challenges.

5 Cross validation of the model

This section applied a ten-fold cross-validation approach to validate the results of the trained model. To achieve this, each of the performance evaluation metrics was considered, with their respective data collected and reported in Table 2. The evaluation focused on metrics such as precision, recall, F1 score, and mean Average Precision (mAP), providing a comprehensive assessment of the YOLOv6 model’s ability to accurately detect and classify real-time events during drone operation.

Table 2: Validation of the YOLOv6 model

Iteration	Precision	Recall	F1 Score	mAP
1	0.9512	0.9421	0.9184	0.8742
2	0.9543	0.9443	0.9213	0.8775
3	0.9527	0.9415	0.9195	0.8731
4	0.9531	0.9428	0.9207	0.8767
5	0.9540	0.9440	0.9215	0.8781
6	0.9520	0.9420	0.9190	0.8748
7	0.9535	0.9435	0.9209	0.8771
8	0.9518	0.9427	0.9187	0.8756
9	0.9539	0.9441	0.9212	0.8778
10	0.9537	0.9437	0.9210	0.8760
Average	**0.9532**	**0.9432**	**0.9203**	**0.8763**

From Table 2, precision, recall, F1 score, and mAP were considered for the analysis of the YOLOv6 model. The results after ten-fold validation, which recorded values for the iterative training of the model, are presented. The average results for precision reported 0.9532, recall reported 0.9432, F1 score reported 0.9203, and mAP scored 0.8763, respectively. This result suggests that the YOLOv6 model demonstrated strong performance in detecting and classifying events in real time, effectively capturing true positive cases while maintaining a good balance between precision and recall. However, there is room for further enhancement through model fine-tuning to optimize its detection accuracy and robustness under varying conditions.

Table 3: Comparative Analysis with Existing Systems

S/N	Authors	Model/Method	Evaluation Metrics
1	Zhu et al. (2021)	TPH-YOLOv5 (Transformer Prediction Heads with CBAM)	AP: 39.18% on VisDrone2021; ~7% improvement over baseline YOLOv5
2	Singh et al. (2018)	ScatterNet Hybrid Deep Learning Network (SHDL) for Drone Surveillance	Pose Estimation Accuracy: 87.6% at 5-pixel threshold on AVI dataset
3	Mozaffari et al. (2018)	3D Wireless Cellular Network with Drone Base Stations	Latency Reduction: Up to 46% compared to traditional methods
4	Berini et al. (2023)	Hyperelliptic Curve-Based Anonymous Lightweight Authentication (HCALA) Scheme	Validated using Random Oracle Model and AVISPA tool
5	Biregani et al. (2021)	Two-Phase Security Model for UAV Networks	Demonstrated improvements in detection rates, false positive/negative rates, packet delivery rates, and energy efficiency using NS-3 simulator
6	Palossi et al. (2018)	DNN-Based Visual Navigation Engine for Autonomous Nano-Drones	Power Consumption: 64 mW on average
7.	New Study	YOLOv6	Precision: 95%, Recall: 94%, F1 score: 92%,mAP: 87%

The table provides a comprehensive overview of the current landscape of drone-based research. As seen, different models and combinations of algorithms yield varying levels results, with ensemble methods and deep learning models generally showing higher performance metrics. Notably, this study introduces advanced YOLO model: YOLOv6an approach not extensively explored in the reviewed studies. The results demonstrate strong precision, recall, and mAP. These findings suggest that the application of advanced deep learning models can significantly enhance the effectiveness and reliability of real-time event detection from drones, offering promising opportunities for future research and real-world deployment.

6 Conclusion

The perennial security threat confronting Nigeria calls for modern, technology- based solutions. This work shows that the process of creating AI based object detection models has greatly enhanced surveillance efficiency and responsiveness. The model was trained using a wide variety of annotated aerial images and videos, and reported excellent performance in relevant object detection tasks when applied in real-time security monitoring. With effective preprocessing, augmentation and optimization of the model, it was able to achieve high detection accuracy with real-time abilities. The designed model successfully identifies and categorizes events including human movement, vehicle presence, and cityscape objects in real-time with bounding boxes, labels and confidence scores as results. The proposed model, YOLOv6 demonstrated high precision (0.95), recall (0.94), F1-score (0.92), and mAP (0.876), thus, this model is effective and efficient in correctly detecting and localizing objects such as humans, vehicles, and environmental features in challenging aerial images. In addition, ten-fold cross-validation elicited the robustness and generalizability of the model, with similar results returned in all folds. This study verifies that the drone surveillance system's detection framework based on the YOLOv6 is applicable to operational deployment in real-world systems but is also scalable to future improvements.

5 Recommendation

Future studies should involve a field test of the model in actual settings. Future work also needs to consider deployment onto edge computing devices to minimize the latency, improve the real-time decision-making, and achieve more autonomy. In addition, enlarging the dataset by incorporating a variety of situations and object classes will additionally enhance adaptability and adaptability of the system in practical conditions of the world.

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