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Comparative Assessment of Onboard AI Models for Drone-Based Bird Pest Detection and Rice Loss Reduction

Chisom S. Nwokonko
Department of Electrical and Electronic Engineering,
Imo State University, Owerri

Abstract

Bird pests cause serious rice yield losses, especially during heading and grain-filling. This paper assesses three onboard artificial intelligence model options for drone-based bird pest detection and rice loss reduction. MobileNetV3-SSD, EfficientDet-Lite and YOLOv5-Nano are evaluated as embedded deployment options within a complete monitoring pipeline that includes detection, threat classification, tracking and deterrence decision support. The models are compared using embedded performance metrics, bird monitoring metrics, composite effectiveness factor, estimated rice loss, quantity of rice lost, cost of rice lost and annual financial savings. MobileNetV3-SSD records the lowest combined operational latency of 78.20 ms, while YOLOv5-Nano records the highest early warning accuracy of 87.90%, the highest CEF of 0.84, the lowest estimated rice loss of 1.23% and the highest annual saving of ₦1,294,731,152.06. These results indicate that YOLOv5-Nano is the preferred onboard option when overall deterrence effectiveness, rice loss reduction and financial savings are the main deployment priorities.

Keywords: drone-based agriculture; bird pest deterrence; rice loss reduction; MobileNetV3-SSD; EfficientDet-Lite; YOLOv5-Nano; embedded AI; computer vision.

1. Introduction

Rice is an important staple crop, but bird pest invasion continues to reduce the quantity of grain harvested from many farms. The problem is more serious in open rice fields because pest birds can enter the farm in flocks, feed quickly and leave before human guards can respond. Traditional control methods such as scarecrows, human shouting, stones, reflective tapes and periodic noise makers are useful only for short periods. Birds often become used to these static methods, and large farms require many human guards to maintain constant coverage.

Drone-based monitoring provides a better response because the drone can patrol the rice field, detect bird movement from the air and move toward the target before the birds settle on the crop. The effectiveness of this approach depends on the artificial intelligence model used on the drone. The model must detect birds in real time, support classification of harmful birds, provide track information for pursuit and operate under the power and memory limits of the onboard device. Heavy models may provide high accuracy, but they are not always practical for drone deployment. Lightweight models therefore need to be assessed not only by accuracy, but also by latency, frame rate, energy demand and economic effect on rice loss reduction.

This paper contributes three main items. First, it presents a complete onboard drone-based AI pipeline for rice bird pest detection, tracking and deterrence. Second, it compares MobileNetV3-SSD, EfficientDet-Lite and YOLOv5-Nano under embedded deployment conditions using both technical and monitoring metrics. Third, it links the composite effectiveness factor of each model to rice loss reduction and financial savings so that model selection is based on practical farm value, not only detection accuracy.

2. Related Work and Research Gap

Bird pest control in rice production has traditionally relied on physical, acoustic and visual deterrents. These methods are affordable, but they suffer from habituation, poor coverage and high labour demand [6], [7]. Sensor-based methods, including passive infrared sensors and microcontroller-controlled buzzers, improve automation but cannot reliably distinguish harmful rice-eating birds from harmless birds. Computer vision methods improve the response by allowing the system to detect birds from image frames and trigger deterrence action only when a bird is present [8], [9]. Recent work on autonomous UAV platforms for agricultural pest bird control also supports the view that drone-based deterrence can overcome the poor coverage and delayed response of fixed deterrent devices [11].

Recent object detection models such as YOLO, SSD and EfficientDet have improved real-time detection in image-based monitoring tasks [1], [4], [8], [10]. MobileNet-based SSD models are attractive for embedded deployment because the backbone is lightweight [2], [4]. EfficientDet-Lite uses efficient multi-scale feature fusion and is designed for edge devices [1]. YOLOv5-Nano is also designed for real-time operation with a small model size [3]. The remaining gap is the need to compare these onboard models using a combined view of detection speed, accuracy, resource use, tracking support and financial benefit. This paper addresses that gap by presenting a harmonized evaluation of the three onboard options in a rice bird pest monitoring context. Recent reviews of AI-powered UAV technologies in precision agriculture further show that onboard perception, lightweight models and standardized evaluation are important for practical field deployment [12].

3. Methodology

3.1 System Model

The proposed system consists of a drone-mounted camera, an onboard AI processing unit, a bird classification and tracking stage, a deterrence command stage and a base station for monitoring and logging. The drone captures aerial frames over the rice field. The selected onboard detector returns bounding boxes and confidence scores for visible birds. The detection output is passed to the threat classification stage to help separate harmful rice pest birds from non-target birds. The tracker then estimates target movement and supplies the location needed for drone pursuit and deterrence action. The tracker follows the tracking-by-detection principle used in SORT-like systems [5]. Field records are also sent to the base station for reporting, rice loss estimation and later model validation.

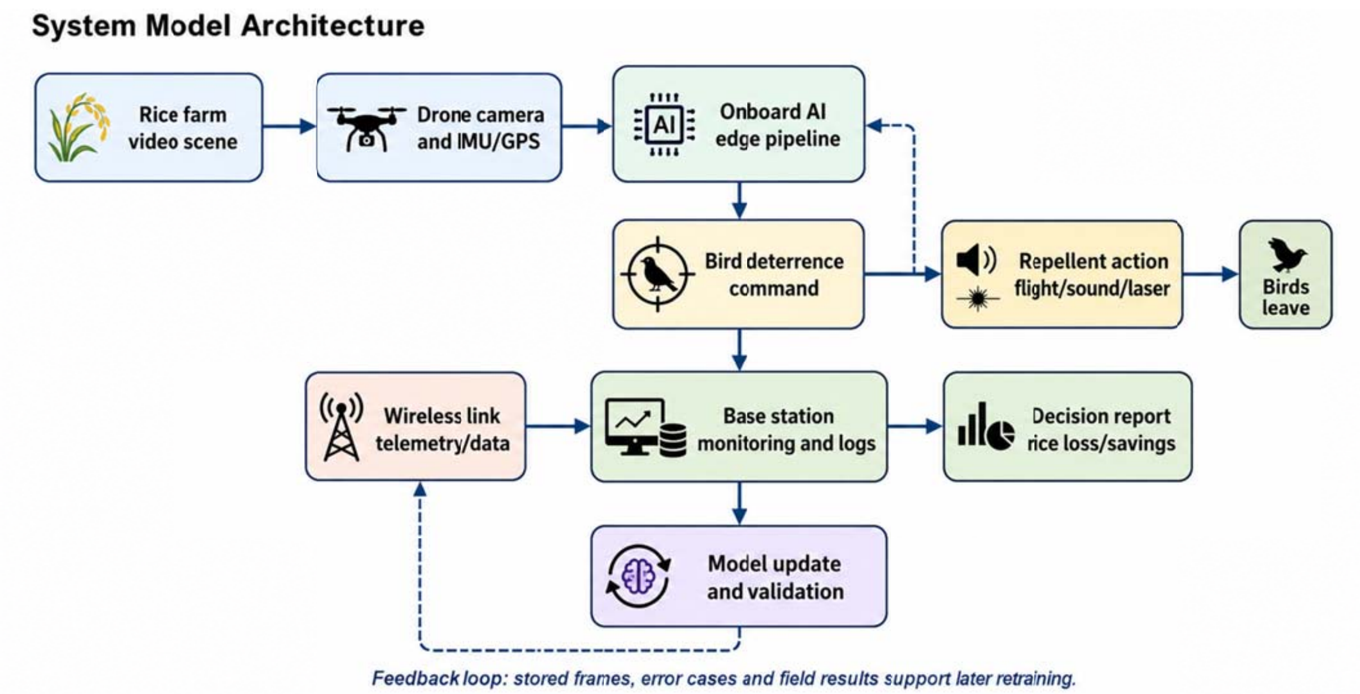

Figure 1. System model architecture for the drone-based rice bird pest monitoring and deterrence system.

3.2 Data and Preprocessing

The evaluation uses dataset groups selected for bird detection, bird classification and drone-based monitoring. The detection task is supported with drone and distant bird detection data, including the Distant Bird Detection Dataset and the Roboflow Drone-Bird Dataset. The classification task is supported with bird species image data, including CUB-200-2011 and NABirds, so that the pipeline can distinguish harmful rice pest birds from non-target birds. Video-frame sequences and detection outputs are used to assess tracking, target distance error and time-to-detection. After preprocessing and augmentation, the available data are organized into training, validation and test partitions using a 70:15:15 split. The training partition is used for model learning, the validation partition is used for model tuning and the test partition is kept separate from training and validation so that the reported comparison is based on unseen data.

The data preparation process includes frame resizing, image quality checking, contrast improvement, normalization and augmentation. Augmentation covers scale change, horizontal flipping, brightness variation, contrast variation and blur simulation because drone frames may contain small targets, motion blur, illumination change and complex rice field backgrounds. The embedded assessment assumes a drone-side processor with limited memory, limited energy and no discrete GPU. The base station is used only for monitoring, record keeping and later validation. The financial analysis uses a rice production quantity of 8,364.18 tons and a unit rice value of ₦2,392,500.00 per ton.

3.3 Onboard Model Options

Three lightweight onboard options are compared in the study. The model names refer to the detector option used inside the complete drone monitoring pipeline, not to a detection-only system. In each case, the detector is followed by threat classification, target tracking and deterrence decision stages. The same rice loss model is then applied to the composite output of each option.

3.3.1 MobileNetV3-SSD

MobileNetV3-SSD combines a lightweight MobileNetV3 feature extraction backbone with SSD detection heads [2], [4]. The backbone extracts compact multi-scale visual features from drone frames. SSD heads use these features to estimate bounding boxes and bird confidence scores. The model is suitable for onboard use because it has low memory demand and low inference latency.

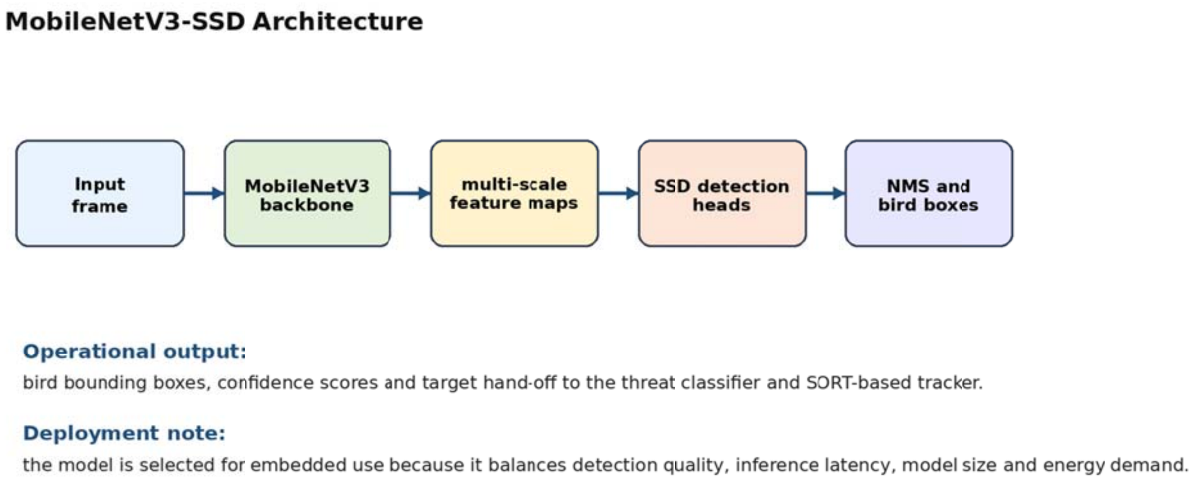

Figure 2. MobileNetV3-SSD model architecture used in the onboard bird monitoring pipeline.

Figure 2 shows that MobileNetV3-SSD uses a lightweight MobileNetV3 backbone to extract compact features before SSD detection heads generate bird bounding boxes for the monitoring pipeline.

3.3.2 EfficientDet-Lite

EfficientDet-Lite is a lightweight object detection model derived from the EfficientDet family [1]. It uses an EfficientNet-Lite backbone for feature extraction and a Bi-directional Feature Pyramid Network for multi-scale feature fusion. This structure helps the detector recognize birds that appear at different distances and sizes in drone images. Classification and box regression heads then produce bird labels, confidence scores and bounding boxes.

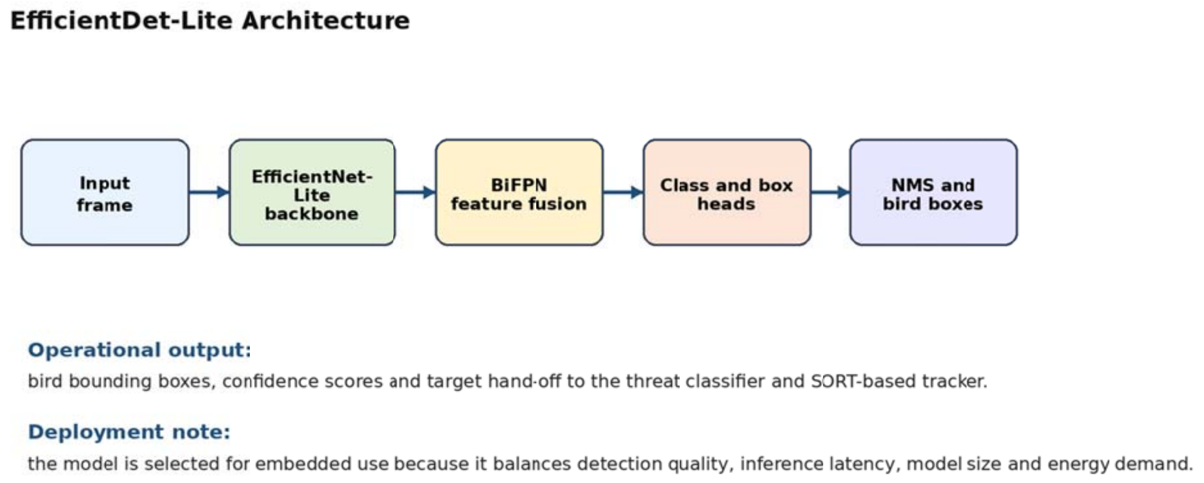

Figure 3. EfficientDet-Lite model architecture used in the onboard bird monitoring pipeline.

Figure 3 shows that EfficientDet-Lite uses an EfficientNet-Lite backbone and BiFPN feature fusion to improve the detection of birds appearing at different image scales.

3.3.3 YOLOv5-Nano

YOLOv5-Nano is a compact one-stage detector designed for real-time inference on devices with limited resources [3]. Its design follows the broader YOLO family of one-stage detectors [8], [10]. The model uses a small backbone, a feature aggregation neck and YOLO detection heads. Its single-stage design allows fast detection and makes it attractive for drone-based response where the system must identify birds before damage occurs.

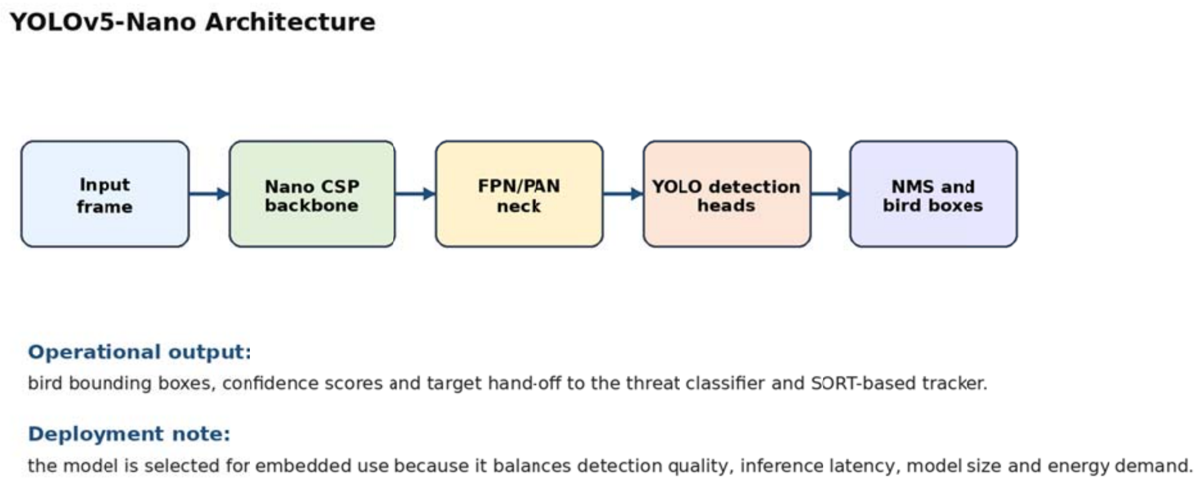

Figure 4. YOLOv5-Nano model architecture used in the onboard bird monitoring pipeline.

Figure 4 shows that YOLOv5-Nano uses a compact one-stage detection structure with a small backbone, neck and detection heads to support real-time onboard response.

3.4 Tracking, Threat Decision and Deterrence Logic

After detection, the monitoring pipeline uses the threat class output to decide whether the detected bird should be pursued. This avoids wasting drone energy on birds that are not harmful to rice. The tracker maintains target position across frames and supplies the motion estimate needed for pursuit. The deterrence command is activated when a tracked harmful bird is inside the protected field zone. This creates an early warning and response process rather than a passive detection-only process.

3.5 Composite Effectiveness and Rice Loss Model

The composite effectiveness factor (CEF) summarizes the combined value of early warning accuracy, threat classification, tracking quality, distance error and latency. It is used because one metric alone cannot show whether an onboard model is truly useful for deterrence. A model may be fast but less accurate, while another may be slightly slower but more effective in reducing rice loss. For model m, the CEF is expressed as the weighted normalized score in (1).

$$CEF_m = w_1 EWA_m + w_2 TCA_m + w_3 TQ_m + w_4(1 - DE_{n,m}) + w_5(1 - L_{n,m}) \quad (1)$$

In (1), EWA is early warning accuracy, TCA is threat class accuracy, TQ is tracking quality, DE_n is normalized distance error and L_n is normalized latency. The weights sum to 1. This study uses $w_1 = 0.30$, $w_2 = 0.25$, $w_3 = 0.20$, $w_4 = 0.15$ and $w_5 = 0.10$. Higher weights are assigned to early warning accuracy and threat classification because early detection and correct pest identification have the strongest effect on successful deterrence.

$$\sum_{i=1}^{5} w_i = 1 \quad (2$$

Rice loss reduction is estimated from the baseline rice loss and the CEF of each onboard model. The estimated rice loss for a model is computed with (3).

$$RL_m = RL_b(1 - CEF_m) \quad (3)$$

Rice loss reduction is the difference between the baseline rice loss and the estimated model-assisted rice loss. Quantity of rice lost is obtained by multiplying total rice production by the estimated rice loss percentage. Cost of rice lost is obtained by multiplying the quantity of rice lost by the unit price of rice. Annual money saved is the difference between the baseline cost of rice loss and the cost of rice loss after model-assisted deterrence.

4. Results and Discussion

This section presents the result values and explains their meaning for onboard deployment, rice loss reduction and financial savings.

4.1 Embedded Performance of the Onboard Models

Table 1 presents the embedded performance evaluation of the three onboard models. The embedded performance values were evaluated under an onboard deployment assumption representing a resource-constrained drone processing unit, while the financial analysis used the rice production and unit cost values stated in the results section. The embedded performance results show the computational behaviour of the three models when used in the onboard monitoring pipeline. MobileNetV3-SSD has the lowest detection latency, classification latency, tracking latency, RAM usage, model size and energy per inference. This makes it the lightest model for embedded drone implementation. EfficientDet-Lite has a larger processing cost, while YOLOv5-Nano uses more memory and energy but gives stronger overall monitoring performance in later results. The latency values in Table 1 refer to embedded processing latency. The combined operational latency reported in Figure 5 includes additional pipeline overheads, such as frame handling, decision logic and communication-related processing.

Table 1. Embedded performance evaluation for onboard models

Metric	MobileNetV3-SSD	EfficientDet-Lite	YOLOv5-Nano
Detection Latency (ms)	23.49	35.10	31.25
Classification Latency (ms)	8.79	11.05	10.42
Tracking Latency (ms)	6.78	8.12	7.95
End-to-End Pipeline Latency (ms)	39.06	54.27	49.62
FPS (Frames Per Second)	25.60	18.42	20.15
CPU Utilization (%)	9.8	14.2	13.1
RAM Usage (MB)	58.09	94.6	121.3
VRAM Usage (MB)	0.00	0.00	0.00
Model Size (MB)	12	19	27
Energy Per Inference (J)	0.0137	0.028	0.041

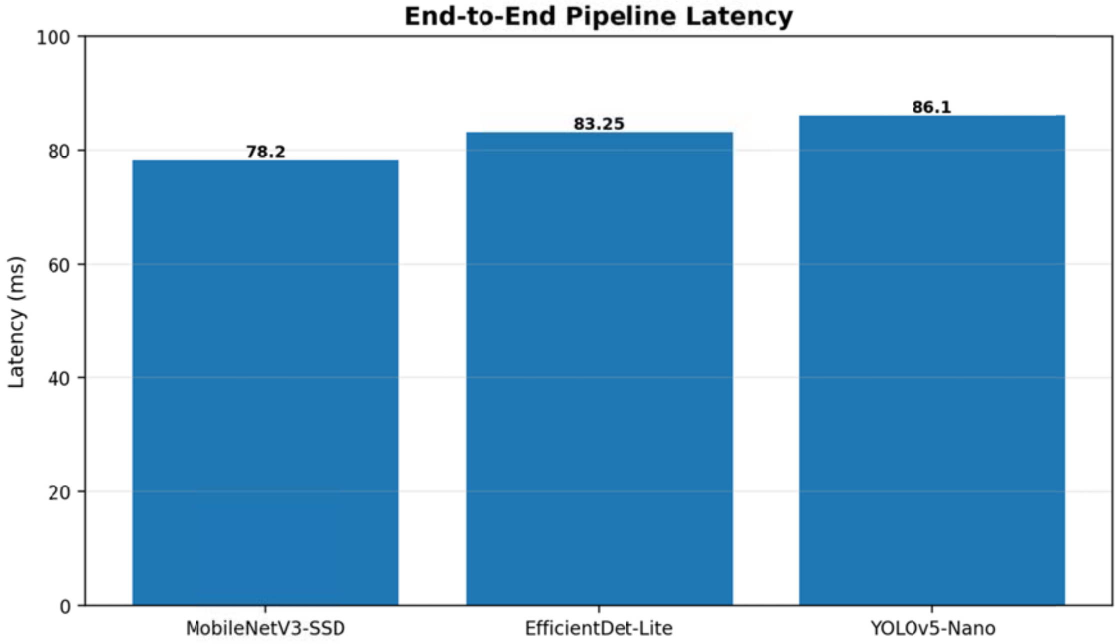

Figure 5. Comparison of the combined end-to-end pipeline latency for the onboard models.

4.2 Bird Monitoring Metrics

Table 2 presents the bird monitoring metrics used to compare detection, classification and tracking behaviour. The bird monitoring metrics combine the effect of detection, classification and tracking. MobileNetV3-SSD records the best time-to-detection at 121.04 ms, while EfficientDet-Lite records 158.32 ms and YOLOv5-Nano records 142.75 ms. Figures 6 and 7 show the time-to-detection and early warning accuracy comparisons. Although MobileNetV3-SSD is faster, YOLOv5-Nano achieves the highest early warning accuracy of 87.90%.

Table 2. Bird monitoring metrics evaluation for onboard models

Model	Time-to-Detection (ms)	Distance Error (m)	Threat Class Accuracy	Early Warning Accuracy
MobileNetV3-SSD	121.04	2.668	0.863	0.850
EfficientDet-Lite	158.32	2.320	0.887	0.872
YOLOv5-Nano	142.75	2.125	0.891	0.879

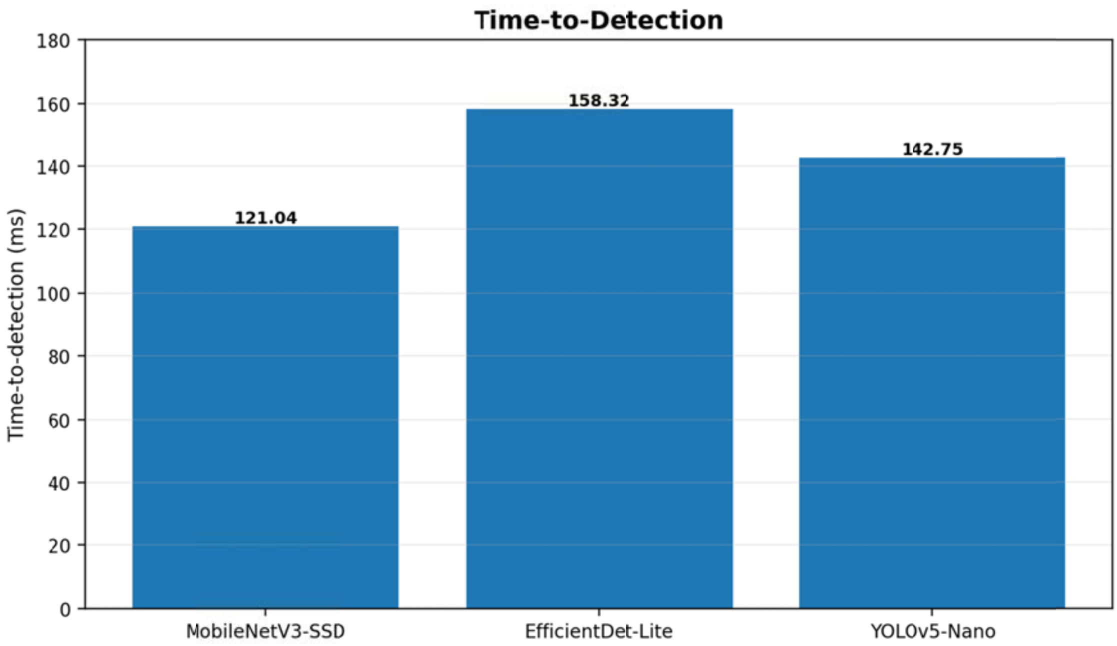

Figure 6. Comparison of the combined time-to-detection for the onboard models.

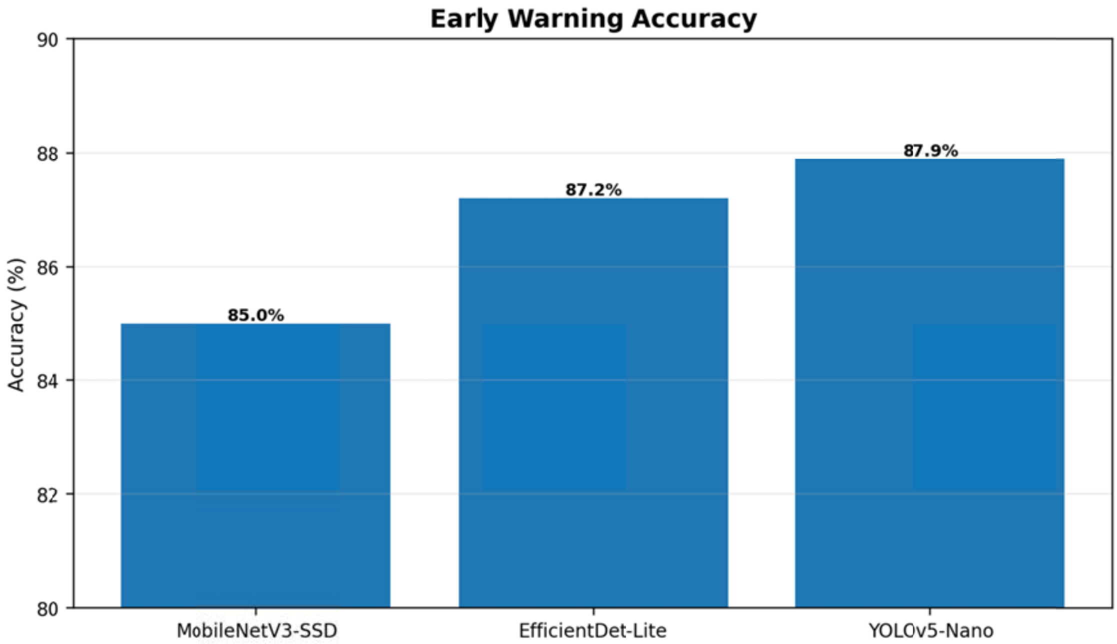

Figure 7. Comparison of the early warning accuracy for the onboard models.

4.3 Composite Effectiveness Factor

Table 3 presents the composite effectiveness factor for the baseline case and the three onboard models. The CEF result confirms the overall strength of YOLOv5-Nano. MobileNetV3-SSD records a CEF of 0.77, EfficientDet-Lite records 0.81 and YOLOv5-Nano records 0.84. The baseline case remains 0.000 because no AI-based monitoring and deterrence action is available. Figure 8 compares the CEF values and shows that YOLOv5-Nano gives the strongest overall balance of detection, warning and deterrence effectiveness.

Table 3. Composite effectiveness factor for onboard bird monitoring models

Model	CEF
Baseline (No AI)	0.000
MobileNetV3-SSD	0.77
EfficientDet-Lite	0.81
YOLOv5-Nano	0.84

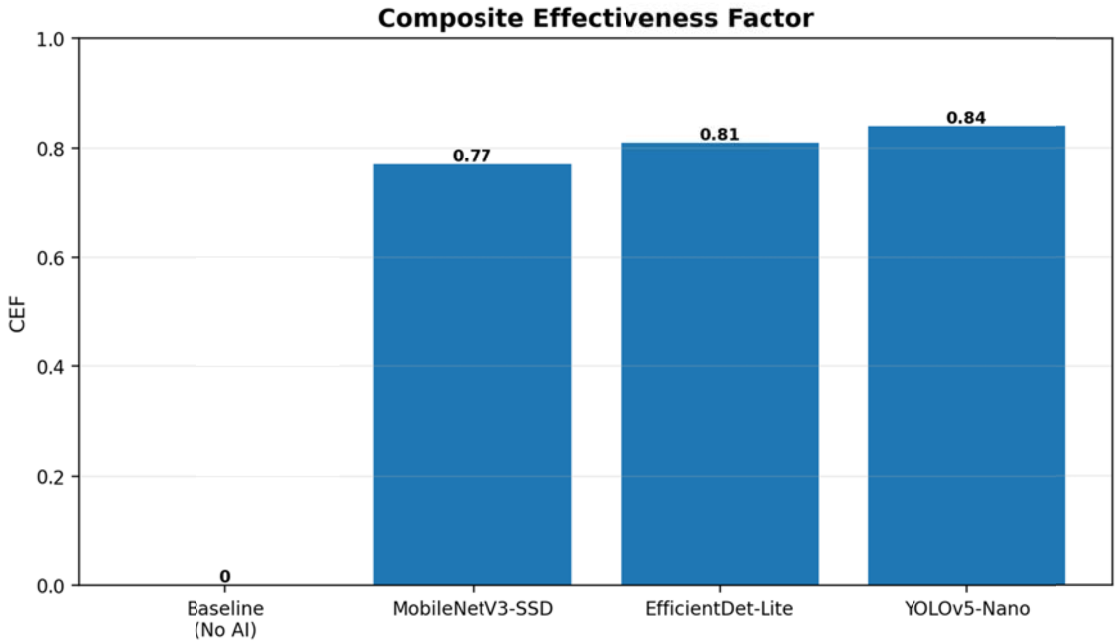

Figure 8. Comparison of the composite effectiveness factor for the onboard models.

4.4 Rice Loss Reduction Performance

Table 4 presents the estimated rice loss and rice loss reduction values for the baseline case and the onboard models. The rice loss results show the practical value of the onboard models. The baseline estimated rice loss is 7.70%. With MobileNetV3-SSD, the loss falls to 1.77%. EfficientDet-Lite reduces the loss to 1.46%, while YOLOv5-Nano gives the lowest estimated loss of 1.23%. Figure 9 compares these loss values and confirms that higher CEF leads to lower estimated rice loss.

Table 4. Rice loss reduction estimation for onboard models

Model	CEF	Estimated Rice Loss (%)	Rice Loss Reduction (%)
Baseline (No AI)	0.000	7.70	0.00
MobileNetV3-SSD	0.77	1.77	5.93
EfficientDet-Lite	0.81	1.46	6.24
YOLOv5-Nano	0.84	1.23	6.47

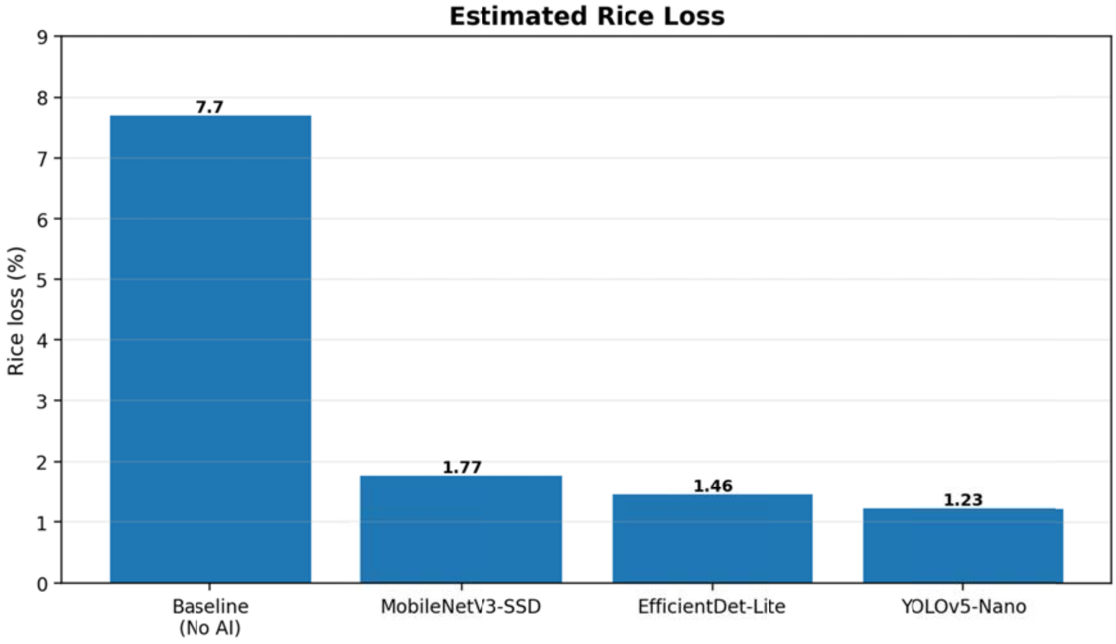

Figure 9. Comparison of the estimated rice loss for the onboard models.

4.5 Cost of Rice Lost and Annual Savings

Tables 5 and 6 present the cost of rice lost and the annual financial savings obtained with the onboard models. The financial results use 8,364.18 tons of rice production and a unit value of ₦2,392,500.00 per ton. Without AI-based monitoring, the estimated cost of rice lost to bird pests is ₦1,540,870,150.05. The cost falls to ₦354,200,021.51 for MobileNetV3-SSD, ₦292,164,989.49 for EfficientDet-Lite and ₦246,138,998.00 for YOLOv5-Nano. Figures 10, 11 and 12 compare the quantity of rice lost, cost of rice lost and annual financial savings. YOLOv5-Nano gives the highest annual savings of ₦1,294,731,152.06, followed by EfficientDet-Lite and MobileNetV3-SSD.

Table 5. Cost of rice lost under onboard model-based bird pest monitoring and deterrence

Model	Estimated Rice Loss (%)	Quantity of Rice Produced (ton)	Quantity of Rice Lost (ton)	Naira/Ton of Rice	Cost of Rice Lost (Naira)
Baseline (No AI)	7.70	8,364.18	644.04	2,392,500.00	1,540,870,150.05
MobileNetV3-SSD	1.77	8,364.18	148.05	2,392,500.00	354,200,021.51
EfficientDet-Lite	1.46	8,364.18	122.12	2,392,500.00	292,164,989.49
YOLOv5-Nano	1.23	8,364.18	102.88	2,392,500.00	246,138,998.00

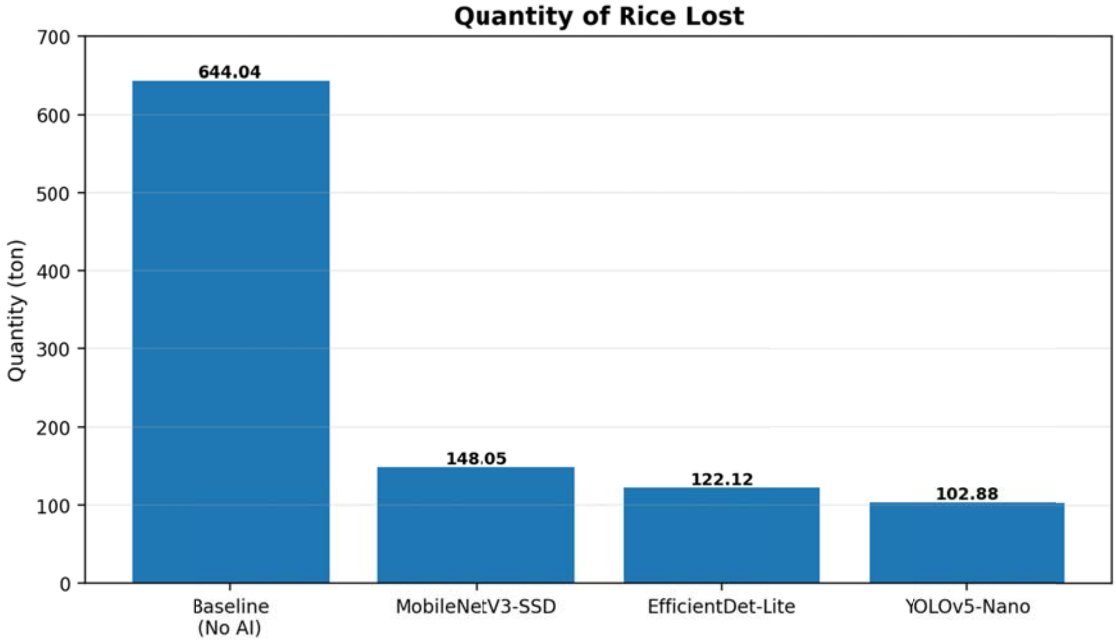

Figure 10. Comparison of the quantity of rice lost due to bird pests for the onboard models.

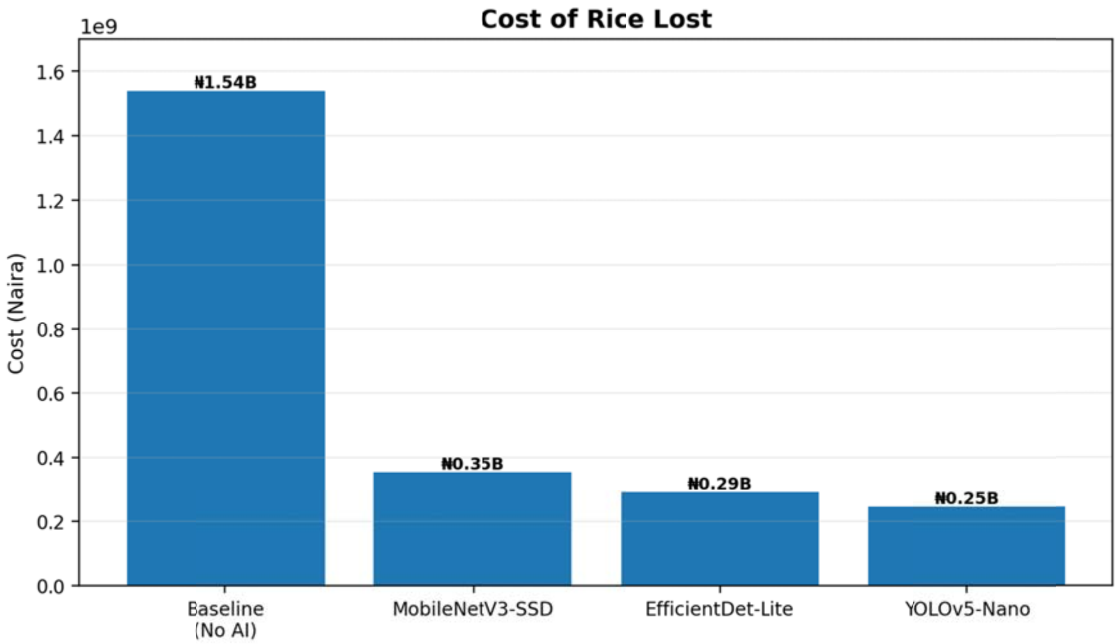

Figure 11. Comparison of the cost of rice lost due to bird pests for the onboard models.

Table 6. Annual financial savings from implementing onboard model-based bird pest monitoring and deterrence

Model	Cost of Rice Lost Due to Bird Pests (Naira)	Amount of Money Saved Annually (Naira)
Baseline (No AI)	1,540,870,150.05	0.00
MobileNetV3-SSD	354,200,021.51	1,186,670,128.55
EfficientDet-Lite	292,164,989.49	1,248,705,160.56
YOLOv5-Nano	246,138,998.00	1,294,731,152.06

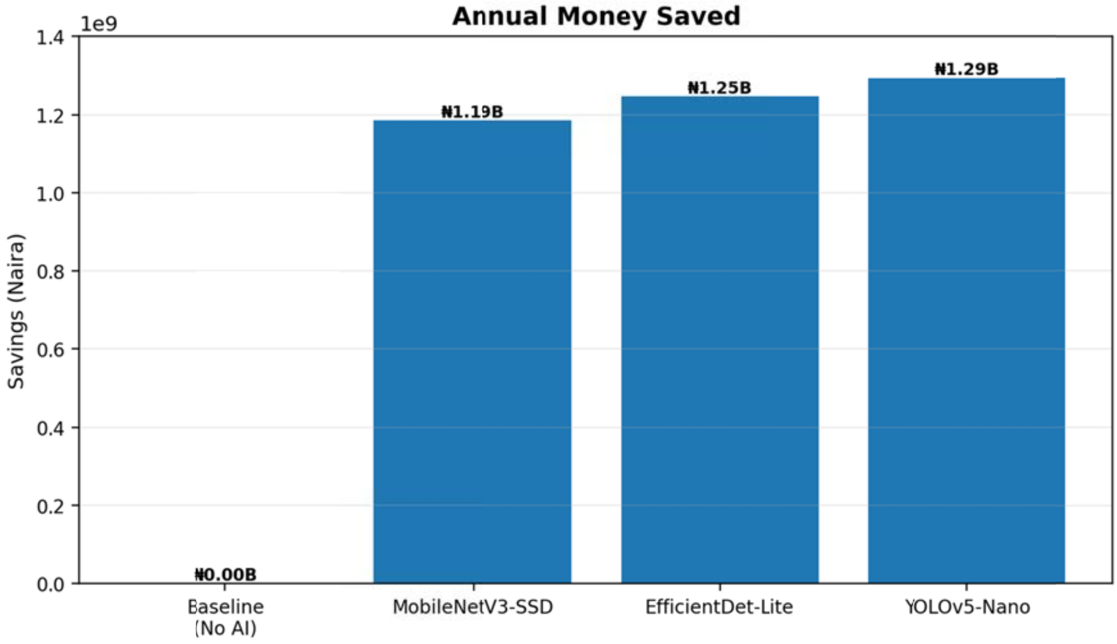

Figure 12. Comparison of annual financial savings for the onboard models.

4.6 Summary of Findings

The results show that the best model depends on the evaluation priority. MobileNetV3-SSD is best when the main priority is low latency, low memory use and low energy per inference. EfficientDet-Lite provides a middle position with better CEF and rice loss reduction than MobileNetV3-SSD. YOLOv5-Nano gives the best overall outcome because it produces the highest early warning accuracy, highest CEF, lowest rice loss and highest annual financial saving. Although YOLOv5-Nano does not have the lowest latency, its latency remains below one second, while its higher CEF gives the best rice loss reduction and annual financial saving.

4.7 Limitations of the Study

The results should be interpreted within the scope of the study. The comparison is based on model evaluation and analytical modelling, not a full physical deployment of the complete system in a rice farm. Real field performance may differ because of changing weather, drone vibration, camera angle, wireless delay, bird flock behaviour, crop growth stage and the local mix of harmful and non-harmful bird species. The rice loss and savings estimates therefore provide a practical decision guide, but they should be refined with field trials before large-scale deployment.

5. Conclusion

This paper assessed three onboard AI model options for drone-based bird pest detection and deterrence in rice farms. MobileNetV3-SSD, EfficientDet-Lite and YOLOv5-Nano were compared using embedded performance metrics, bird monitoring metrics, composite effectiveness factor, rice loss reduction and annual financial savings. The findings show that MobileNetV3-SSD is the fastest and lightest option, but YOLOv5-Nano gives the best overall practical performance. YOLOv5-Nano achieved a CEF of 0.84, reduced estimated rice loss to 1.23%, reduced the quantity of rice lost to 102.88 tons and produced annual savings of ₦1,294,731,152.06. Based on these results, YOLOv5-Nano is recommended as the onboard model for the drone-based rice bird pest monitoring and deterrence system considered in this study.

Future work should test the models on real drone hardware in rice farms, include more local rice pest bird species in the classification dataset and evaluate the long-term response of birds to different deterrence actions. Field validation will also help refine the CEF and improve the accuracy of the financial loss model.

References

[1] M. Tan, R. Pang, and Q. V. Le, "EfficientDet: Scalable and efficient object detection," in Proc. IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 10781-10790, doi: 10.1109/CVPR42600.2020.01079.

[2] A. Howard et al., "Searching for MobileNetV3," in Proc. IEEE/CVF International Conference on Computer Vision, 2019, pp. 1314-1324, doi: 10.1109/ICCV.2019.00140.

[3] G. Jocher et al., "YOLOv5 by Ultralytics: Real-time object detection software repository," GitHub, 2020. [Online]. Available: https://github.com/ultralytics/yolov5. Accessed: Jun. 6, 2026.

[4] W. Liu et al., "SSD: Single shot multibox detector," in Proc. European Conference on Computer Vision, 2016, pp. 21-37, doi: 10.1007/978-3-319-46448-0_2.

[5] A. Bewley, Z. Ge, L. Ott, F. Ramos, and B. Upcroft, "Simple online and realtime tracking," in Proc. IEEE International Conference on Image Processing, 2016, pp. 3464-3468, doi: 10.1109/ICIP.2016.7533003.

[6] E. C. Oerke, "Crop losses to pests," Journal of Agricultural Science, vol. 144, no. 1, pp. 31-43, 2006, doi: 10.1017/S0021859605005708.

[7] Y. De Mey, M. Demont, and M. Diagne, "Estimating bird damage to rice in Africa: Evidence from the Senegal River Valley," Journal of Agricultural Economics, vol. 63, no. 1, pp. 175-200, 2012, doi: 10.1111/j.1477-9552.2011.00323.x.

[8] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 779-788, doi: 10.1109/CVPR.2016.91.

[9] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards real-time object detection with region proposal networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 2017, doi: 10.1109/TPAMI.2016.2577031.

[10] J. Redmon and A. Farhadi, "YOLO9000: Better, faster, stronger," in Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 7263-7271, doi: 10.1109/CVPR.2017.690.

[11] J. Trethowan, Z. Wang, and K. C. Wong, "The viability of a grid of autonomous ground-tethered UAV platforms in agricultural pest bird control," Machines, vol. 11, no. 3, p. 377, 2023, doi: 10.3390/machines11030377.

[12] J. Agrawal and M. Y. Arafat, "Transforming farming: A review of AI-powered UAV technologies in precision agriculture," Drones, vol. 8, no. 11, p. 664, 2024, doi: 10.3390/drones8110664.