Financial Loss Minimization For Drone-Based Bird Pest Deterrence In Rice Farms Using Base-Station Deep Learning Models

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Abstract

This paper evaluates the reported experimental and economic outcomes of base-station deep learning models for drone-based bird pest monitoring and deterrence in rice farms. The drone captures airborne images of the rice field and transmits them to a base station, where the AI model detects birds, supports pest classification, assists target tracking, and informs deterrent action. The evaluation compares Faster R-CNN with ResNet50, Faster R-CNN with ResNet101, and YOLOv7-Large using latency, time-to-detection, threat class accuracy, early warning accuracy, composite effectiveness factor, estimated rice loss, and financial loss. The baseline case without AI gives an estimated rice loss of 644.04 tons per year, valued at 1,540,870,150.05 Naira. Faster R-CNN with ResNet50 reduces the loss to 173.97 tons, while Faster R-CNN with ResNet101 reduces it to 154.74 tons. YOLOv7-Large gives the best result by reducing the rice loss to 83.64 tons and the annual financial loss to 200,113,006.50 Naira. The annual saving obtained with YOLOv7-Large is 1,340,757,143.55 Naira. The results show that the model with the strongest technical performance also provides the highest estimated economic benefit. YOLOv7-Large is therefore recommended for the base-station implementation scenario considered in this paper.

Keywords: bird pest deterrence; drone-based monitoring; rice loss reduction; YOLOv7-Large; Faster R-CNN; base station AI; financial loss minimization.

1. Introduction

Rice farming supports food security and household income in many agricultural communities. A major challenge is that bird pests attack rice during the heading, milky, and grain-filling stages. These attacks reduce harvest quantity and create financial losses for farmers. Traditional methods such as scarecrows, noise-making, and human guarding are still used, but they are labour-intensive and become less effective when birds adapt to them. Without an intelligent system, farmers may waste deterrence resources on birds that do not pose a direct threat to rice production.

Drone-based monitoring offers a more flexible solution because the drone can move across the farm, observe birds from the air, and support quick deterrent action. When this capability is combined with deep learning, the system can detect birds, identify likely pest threats, track their movement, and guide a repellent response. A base station can run heavier and more accurate models than a small onboard drone processor because it has better power and computing resources. The main trade-off is that the base-station approach depends on the communication link between the drone and the ground unit.

This paper evaluates base-station AI models for a drone-based bird pest deterrent system. It also links model performance to the quantity of rice saved and the amount of money saved. The study is important because a technically accurate model is most useful when it also reduces practical farm losses and improves economic return.

1.1 Aim and contributions

The aim of the study is to evaluate deep learning models for drone-based bird pest monitoring in rice farms and to quantify the expected reduction in rice loss and financial loss. The main contributions are: first, an integrated system model for drone-to-base-station bird pest monitoring; second, a corrected explanation of the base-station model results; third, clear model architecture diagrams for the models used in the study; fourth, a defined composite effectiveness factor for comparing practical deterrent performance; and fifth, an economic analysis that connects technical model performance with rice loss reduction.

1.2 Scope and limitation

The study focuses on model-based evaluation and economic loss estimation. It does not build a physical drone, base station, wireless link, or repellent actuator. The drone is treated as the image-acquisition and response platform, while the base station is treated as the computing unit that runs the heavier models. The CUB-200-2011 and NABirds datasets provide useful bird image samples for training and validation, but they do not fully represent Nigerian rice-farm drone imagery. Since CUB-200-2011 and NABirds are not rice-farm-specific drone datasets, field validation using Nigerian rice-farm aerial images is required before full deployment. Future work should therefore include field-collected drone images from local rice farms, real wireless communication delay, and multi-season field validation.

2. Methodology

2.1 System model architecture

The proposed system has five main parts: the rice farm environment, the drone camera, the onboard flight controller, the wireless link, and the base-station AI unit. The drone captures airborne images or video frames of the farm. The frames are either processed locally by a lightweight onboard model or transmitted to the base station for heavier model inference. The base station returns a decision that identifies whether the detected bird is a likely pest threat and whether deterrent action is required.

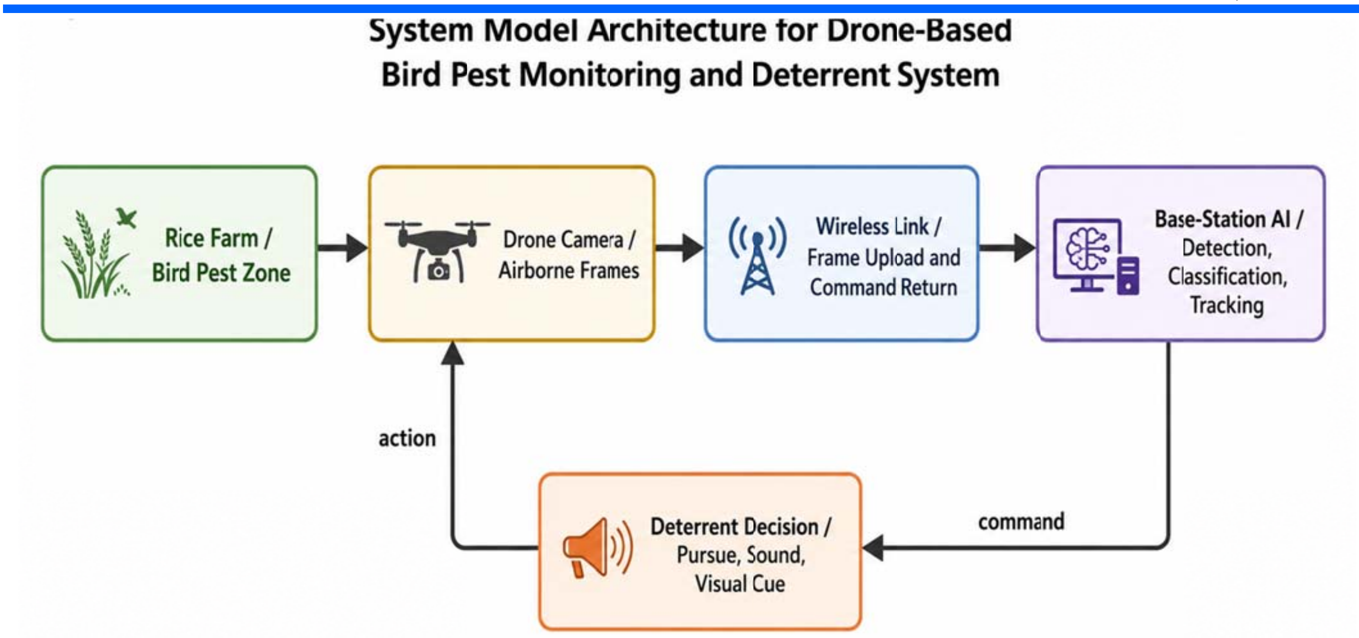

Figure 1. System model architecture for the drone-based bird pest monitoring and deterrent system.

2.2 Dataset preparation and preprocessing

The study uses the Caltech-UCSD Birds-200-2011 and NABirds datasets as reported in the original results. CUB-200-2011 contains 11,788 images from 200 bird species, while NABirds contains 48,562 annotated images from 404 bird species. The datasets support bird recognition and model validation. Since the datasets are not rice-farm-specific drone datasets, they are treated as proxy bird-image datasets for the model evaluation. The reported results should therefore be read as controlled model-evaluation results and not as final field-deployment measurements.

The preprocessing stage includes image cleaning, quality screening, resizing, annotation standardization, normalization, and data augmentation. The available images were divided into training and validation subsets using the reported 0.80 to 0.20 ratio. Augmentation improves robustness to different viewpoints, object scales, illumination levels, and background conditions. These steps make the images more suitable for detection and classification under drone-based monitoring assumptions.

2.3 Experimental setup

The study used a common validation setting for all compared models. The models were evaluated using resized input images, pretrained weights, transfer learning, an 80:20 train-validation split, and the same performance metrics for all compared models.

The validation procedure applied the same input preparation, fine-tuning process, and evaluation criteria across the compared models. The measured metrics include detection latency, classification latency, tracking latency, end-to-end pipeline latency, frames per second, CPU utilization, memory usage, model size, energy per inference, time-to-detection, distance error, threat class accuracy, and early warning accuracy.

2.4 Integrated AI processing pipeline

The processing pipeline begins with image acquisition from the drone camera. The frame is preprocessed and passed to the detection model. The detector localizes birds in each frame and returns bounding boxes and confidence scores. The classifier identifies whether each detected bird belongs to a rice-pest category or a non-target category. The tracker maintains the movement path of confirmed pest birds across consecutive frames. The final decision stage issues a command for drone pursuit, sound emission, visual deterrence, or another repellent response depending on the design of the field system.

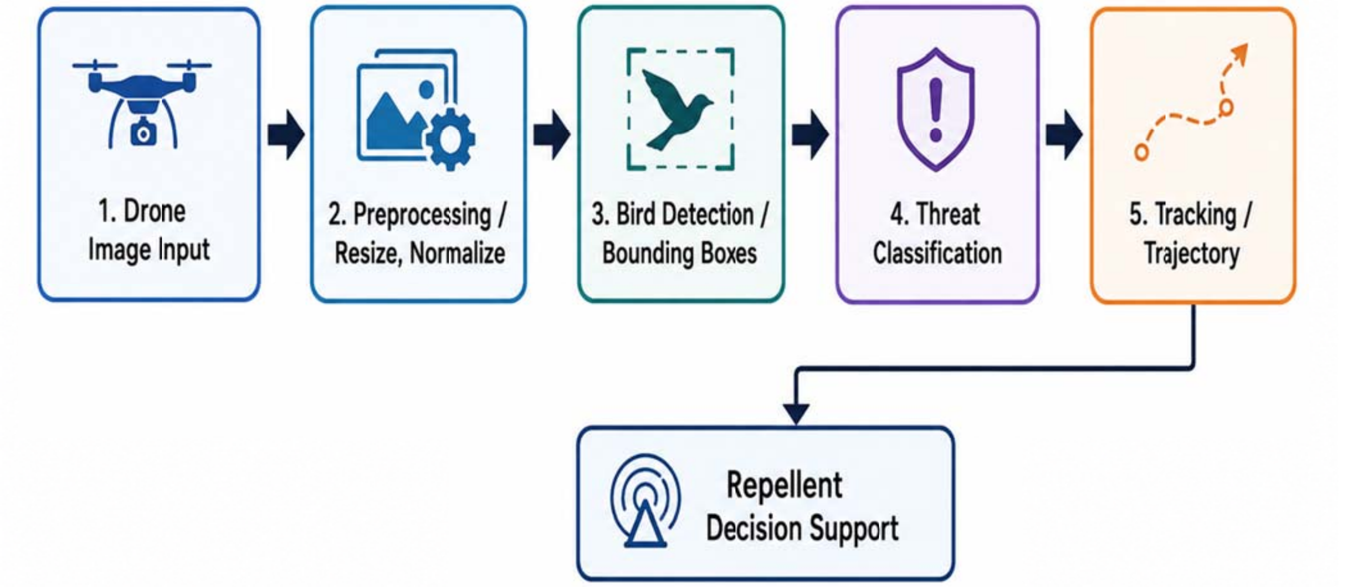

Figure 2. Integrated AI processing pipeline for bird detection, classification, tracking, and deterrent decision support.

2.5 Tracking method used in the monitoring pipeline

The tracking stage follows a tracking-by-detection structure. Each frame is first processed by the selected detector. The resulting bounding boxes are then associated with earlier detections to maintain the movement path of confirmed pest birds across consecutive frames. For the integrated evaluation, the tracking stage is treated as a tracking-by-detection module whose latency is included in the end-to-end pipeline latency.

2.6 Base-station model architectures

The base-station models evaluated in the study are Faster R-CNN with ResNet50, Faster R-CNN with ResNet101, and YOLOv7-Large. The base station can host these models because it is not directly constrained by drone battery capacity. Faster R-CNN uses a two-stage detection process in which region proposals are first generated and later refined for object classification and localization. The ResNet50 and ResNet101 backbones provide feature extraction at different depths. YOLOv7-Large uses a one-stage detection structure that predicts bounding boxes and class confidence directly from multi-scale feature maps. This makes it faster for time-sensitive monitoring.

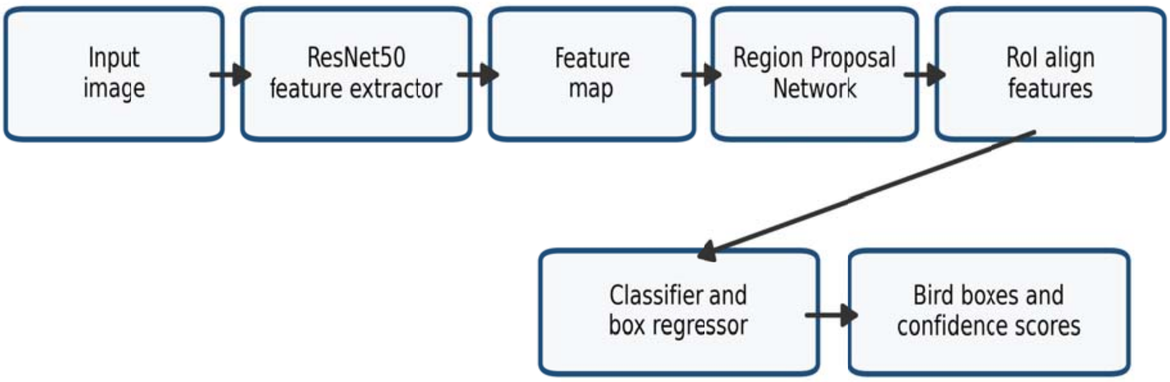

Figure 3. Model architecture diagram for Faster R-CNN with ResNet50 Backbone.

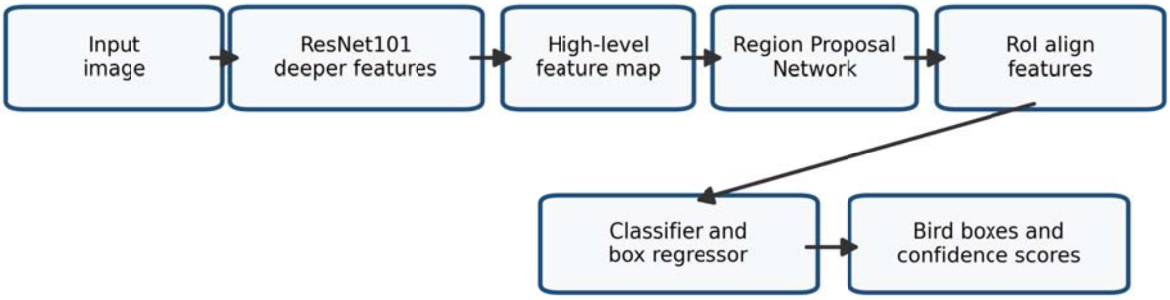

Figure 4. Model architecture diagram for Faster R-CNN with ResNet101 Backbone.

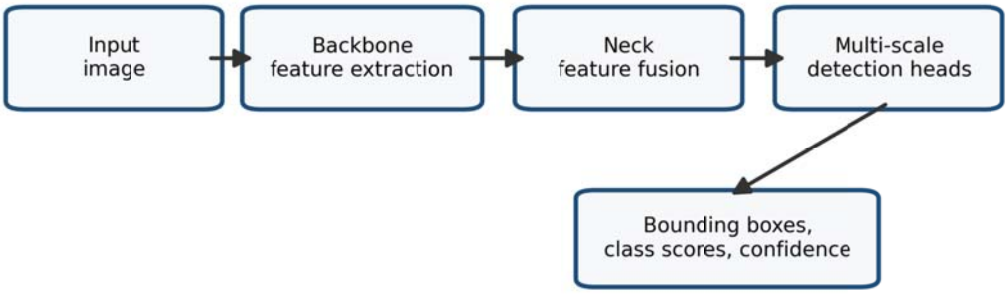

Figure 5. Model architecture diagram for YOLOv7-Large.

2.7 Onboard model architectures used for comparison

The wider study also compares the base-station models with lightweight onboard models. These onboard models are MobileNetV3-SSD, EfficientDet-Lite, and YOLOv5-Nano. They are designed for embedded inference and are included to place the base-station results in the wider context of drone deployment. They are not the primary basis for selecting the best base-station model.

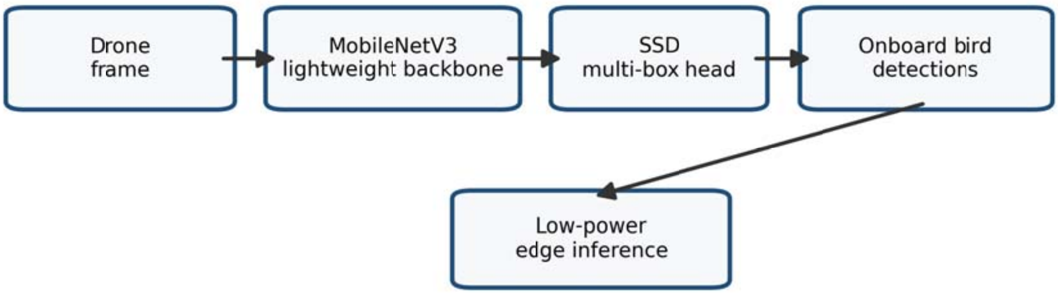

Figure 6. Model architecture diagram for MobileNetV3-SSD onboard detection.

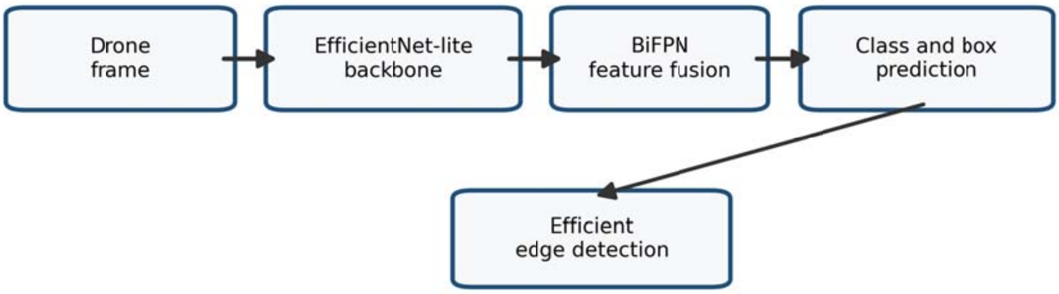

Figure 7. Model architecture diagram for EfficientDet-Lite onboard detection.

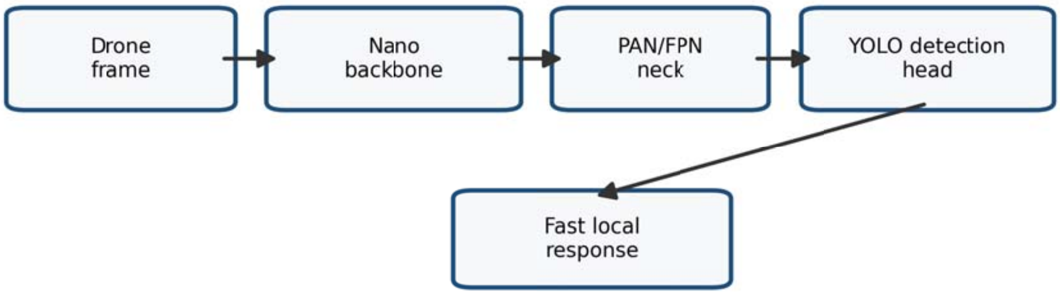

Figure 8. Model architecture diagram for YOLOv5-Nano onboard detection.

2.8 Composite effectiveness factor

A single performance metric is useful because a rice bird deterrent model must be fast, accurate, and stable. Accuracy alone is not enough. A model with high accuracy but slow response may allow birds to settle and cause damage before deterrent action is completed. The composite effectiveness factor (CEF) combines early warning accuracy, threat classification accuracy, latency score, and distance-error score.

$$\mathrm{CEF} = 0.35A_{ew} + 0.25A_{tc} + 0.20L_{\mathrm{score}} + 0.20D_{\mathrm{score}} \tag{1}$$

In Equation (1), A_ew is the normalized early warning accuracy, A_tc is the normalized threat classification accuracy, L_score is the normalized latency score, and D_score is the normalized distance-error score. Higher weight is assigned to early warning accuracy because early detection determines whether the drone can repel birds before meaningful crop damage occurs. A higher CEF value indicates better overall deterrent suitability because it combines accurate early warning, correct pest threat classification, lower latency, and lower tracking distance error.

2.9 Rice loss and financial loss computation

The baseline production quantity used in the reported results is 8,364.18 tons. The baseline rice loss due to bird pest is 7.70%, which corresponds to 644.04 tons. The unit cost of rice used in the computation is 2,392,500.00 Naira per ton. The quantity of rice lost, cost of rice lost, and annual saving are computed using Equations (2) to (4).

$$Q_{\mathrm{lost},i} = Q_{\mathrm{prod}} \times \frac{L_i}{100} \tag{2}$$

$$C_{\mathrm{lost},i} = Q_{\mathrm{lost},i} \times C_{\mathrm{ton}} \tag{3}$$

$$S_i = C_{\mathrm{lost,baseline}} - C_{\mathrm{lost},i} \tag{4}$$

3. Results and discussion

3.1 Base-station performance results

The base-station performance results are presented in Table 1. The results cover detection latency, classification latency, tracking latency, end-to-end pipeline latency, frames per second, resource usage, model size, and energy per inference.

Table 1. Performance evaluation of base-station models.

Metric	Faster R-CNN with ResNet50 Backbone	Faster R-CNN with ResNet101 Backbone	YOLOv7-Large
Detection latency (ms)	52.62	68.45	39.75
Classification latency (ms)	27.30	34.12	22.10
Tracking latency (ms)	18.53	21.85	12.65

Metric	Faster R-CNN with ResNet50 Backbone	Faster R-CNN with ResNet101 Backbone	YOLOv7-Large
End-to-end pipeline latency (ms)	98.44	124.42	74.50
FPS (frames per second)	10.16	8.05	13.42
CPU utilization (%)	7.70	9.20	8.50
RAM usage (MB)	58.09	58.09	121.30
VRAM usage (MB)	898.74	1,024.80	645.50
Model size (MB)	312.00	352.00	142.00
Energy per inference (J)	0.1477	0.1860	0.0890

The Faster R-CNN with ResNet101 Backbone has the highest end-to-end latency of 124.42 ms. This is expected because the deeper ResNet101 backbone carries more computational load. YOLOv7-Large gives the lowest end-to-end latency of 74.50 ms and the highest throughput of 13.42 frames per second. This gives it a stronger practical advantage for fast bird monitoring and deterrent response.

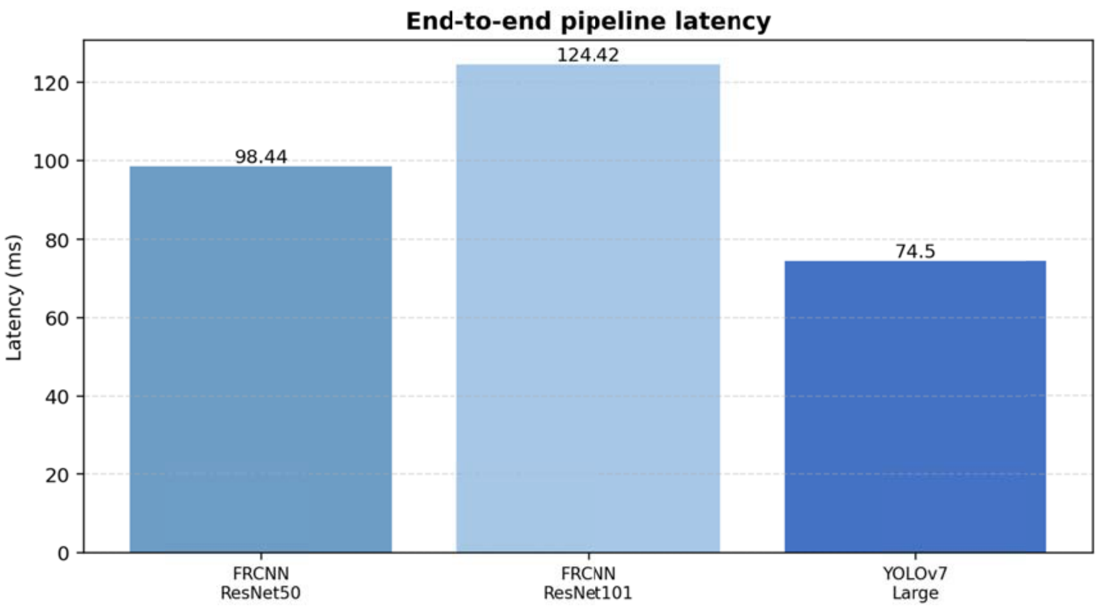

Figure 9. Comparison of end-to-end pipeline latency for base-station models.

3.2 Bird monitoring metrics

The monitoring metrics are presented in Table 2. These metrics show how each model supports fast bird detection, tracking accuracy, threat classification, and early warning response.

Table 2. Bird monitoring metric evaluation for base-station models.

Model	Time-to-detection (ms)	Distance error (m)	Threat class accuracy	Early warning accuracy
Faster R-CNN with ResNet50 Backbone	215.48	4.92	0.918	0.912
Faster R-CNN with ResNet101 Backbone	251.77	4.69	0.927	0.930
YOLOv7-Large	187.33	4.25	0.938	0.940

YOLOv7-Large gives the best time-to-detection value of 187.33 ms, the lowest distance error of 4.25 m, the highest threat class accuracy of 0.938, and the highest early warning accuracy of 0.940. Faster R-CNN with

ResNet101 improves accuracy relative to Faster R-CNN with ResNet50, but it also increases time-to-detection. For a deterrent system, the speed of warning matters because response must occur before birds settle and feed on the rice.

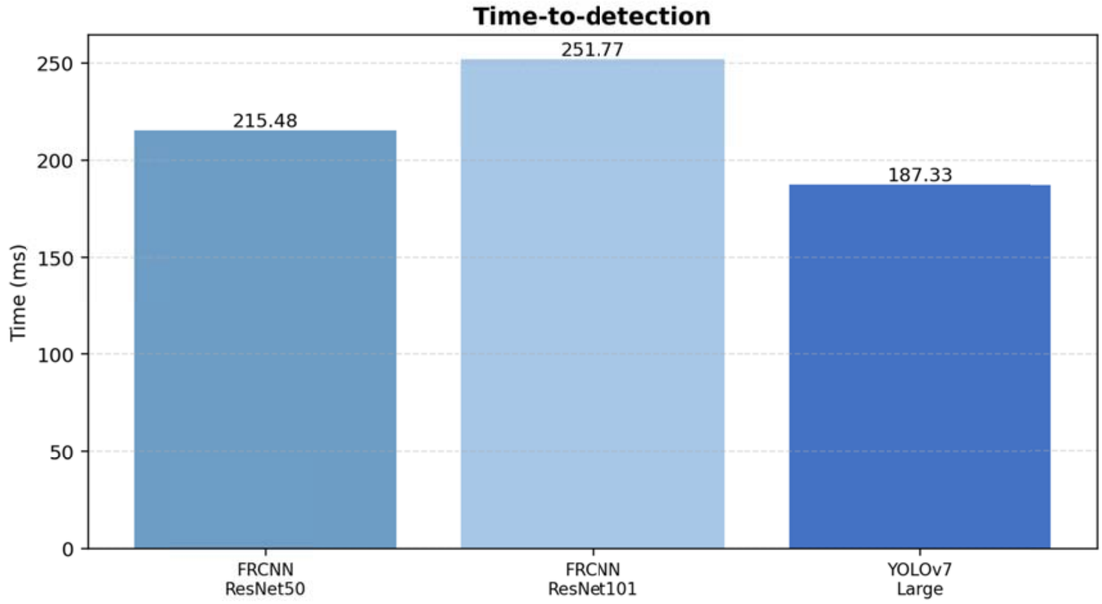

Figure 10. Comparison of time-to-detection for base-station models.

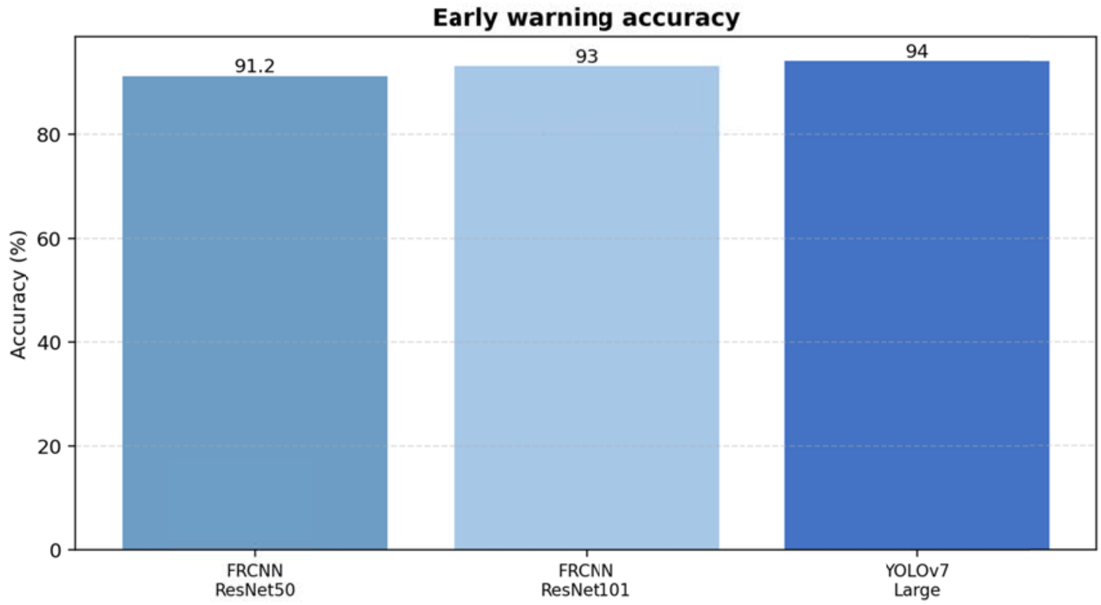

Figure 11. Comparison of early warning accuracy for base-station models.

3.3 Composite effectiveness factor

The CEF results are presented in Table 3. The baseline has no AI support, so its CEF is 0.000. Among the base-station models, YOLOv7-Large has the highest CEF of 0.87. Faster R-CNN with ResNet101 has a CEF of 0.76, while Faster R-CNN with ResNet50 has a CEF of 0.73.

Table 3. Composite effectiveness factor for base-station bird monitoring models.

Model	CEF
Baseline (No AI)	0.000

Model	CEF
Faster R-CNN (ResNet50)	0.73
Faster R-CNN (ResNet101)	0.76
YOLOv7-Large	0.87

The result indicates that YOLOv7-Large gives the best balance of speed, early warning accuracy, tracking support, and threat classification. This explains why it also provides the best rice loss and financial loss reduction in the later economic analysis.

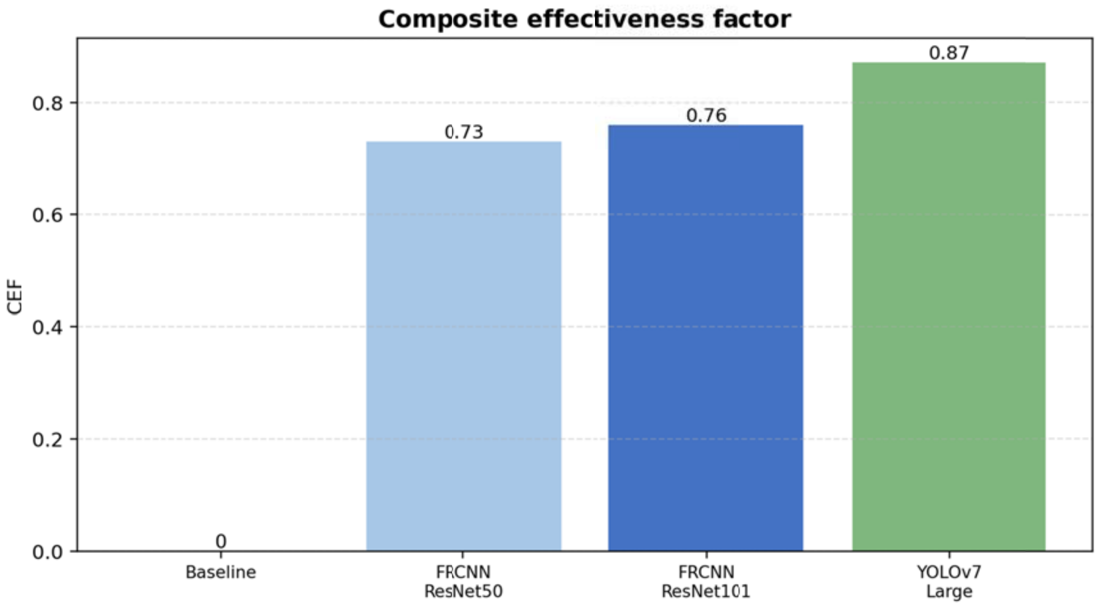

Figure 12. Comparison of composite effectiveness factor for base-station models.

3.4 Rice loss reduction results

The estimated rice loss reduction results are shown in Table 4. The column previously labelled as rice loss reduction is corrected here as percentage-point reduction because it is computed as the difference between the baseline loss percentage and the model-based loss percentage. A relative reduction column is also added for clarity.

Table 4. Rice loss reduction estimation for base-station models.

Model	CEF	Estimated rice loss (%)	Rice loss reduction (percentage-point)	Relative rice loss reduction (%)
Baseline (No AI)	0.000	7.70	0.00	0.00
Faster R-CNN (ResNet50)	0.73	2.08	5.62	72.99
Faster R-CNN (ResNet101)	0.76	1.85	5.85	75.97
YOLOv7-Large	0.87	1.00	6.70	87.01

The baseline estimated rice loss is 7.70%. Faster R-CNN with ResNet50 reduces the estimated loss to 2.08%, while Faster R-CNN with ResNet101 reduces it to 1.85%. YOLOv7-Large gives the lowest estimated rice loss of 1.00%. This corresponds to a 6.70 percentage-point reduction and an 87.01% relative reduction compared with the baseline.

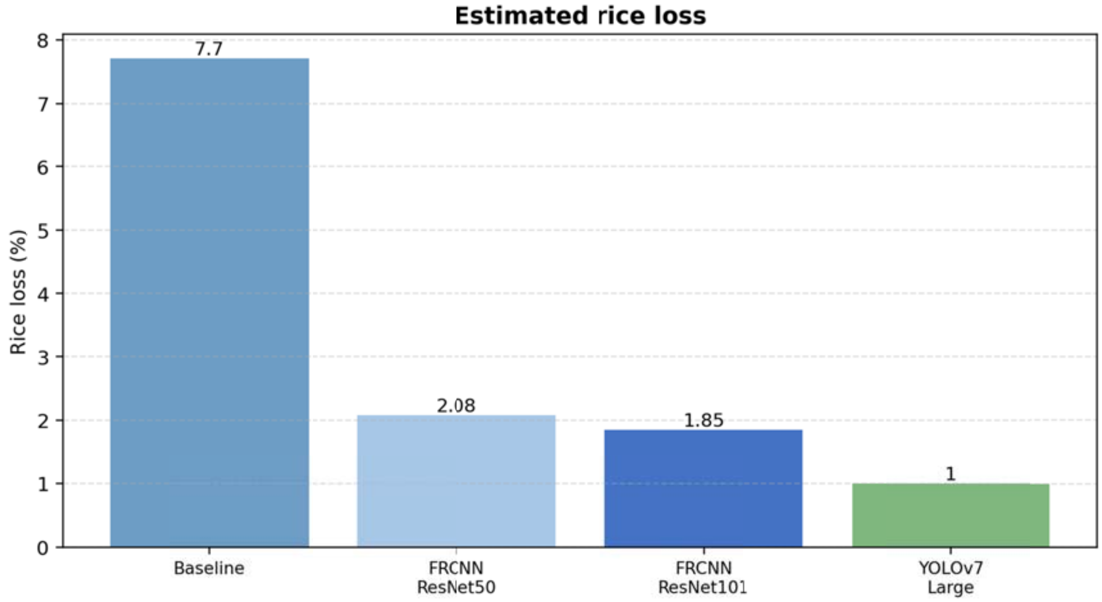

Figure 13. Comparison of estimated rice loss for base-station models.

3.5 Cost of rice lost

The financial loss results are presented in Table 5. The baseline condition without AI gives a loss of 644.04 tons of rice per year. At 2,392,500.00 Naira per ton, this corresponds to 1,540,870,150.05 Naira. Faster R-CNN with ResNet50 reduces the rice lost to 173.97 tons. Faster R-CNN with ResNet101 reduces it to 154.74 tons. YOLOv7-Large gives the best result by reducing the rice lost to 83.64 tons, with an estimated financial loss of 200,113,006.50 Naira.

Table 5. Estimated cost of rice lost due to bird pest for base-station models.

Model	Estimated rice loss (%)	Quantity of rice produced (ton)	Quantity of rice lost due to bird pest (ton)	Unit cost per ton (Naira)	Estimated cost of rice lost due to bird pest (Naira)
Baseline (No AI)	7.70	8,364.18	644.04	2,392,500.00	1,540,870,150.05
Faster R-CNN (ResNet50)	2.08	8,364.18	173.97	2,392,500.00	416,235,053.52
Faster R-CNN (ResNet101)	1.85	8,364.18	154.74	2,392,500.00	370,209,062.03
YOLOv7-Large	1.00	8,364.18	83.64	2,392,500.00	200,113,006.50

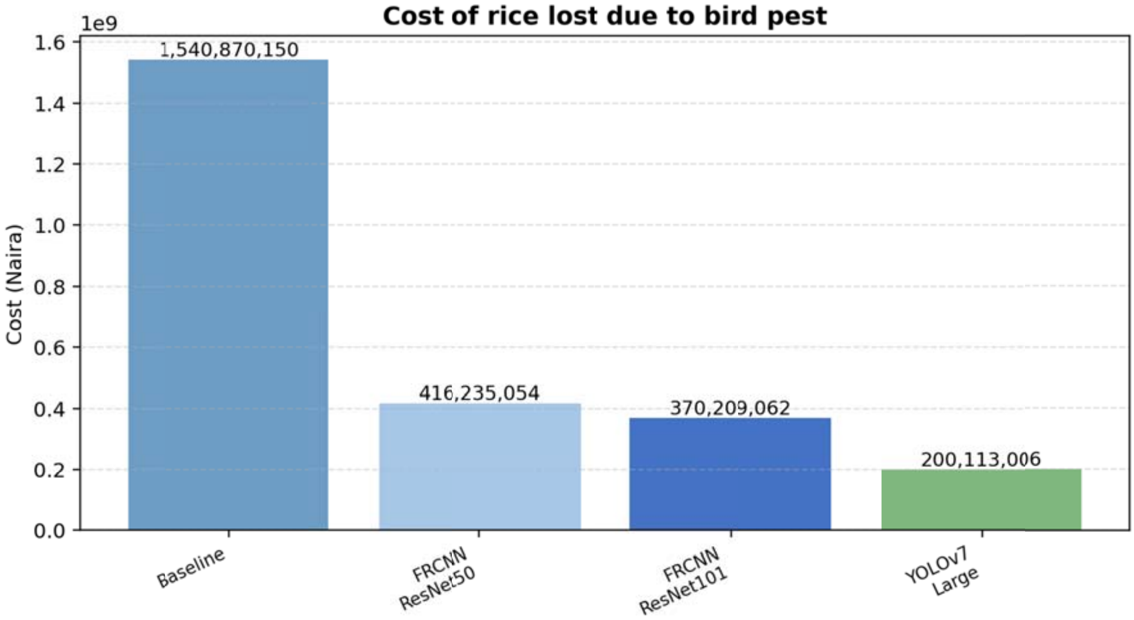

Figure 14. Comparison of the cost of rice lost due to bird pest for base-station models.

3.6 Annual financial saving

The annual saving is computed by subtracting the estimated cost of rice lost after model-based deterrence from the baseline cost of rice lost. The results are shown in Table 6. Faster R-CNN with ResNet50 saves 1,124,635,096.53 Naira per year. Faster R-CNN with ResNet101 saves 1,170,661,088.03 Naira per year. YOLOv7-Large saves 1,340,757,143.55 Naira per year, which is the highest saving among the base-station models.

Table 6. Annual money saved by implementing the bird pest deterrent system.

Model	Estimated cost of rice lost due to bird pest (Naira)	Annual money saved (Naira)
Baseline (No AI)	1,540,870,150.05	0.00
Faster R-CNN (ResNet50)	416,235,053.52	1,124,635,096.53
Faster R-CNN (ResNet101)	370,209,062.03	1,170,661,088.03
YOLOv7-Large	200,113,006.50	1,340,757,143.55

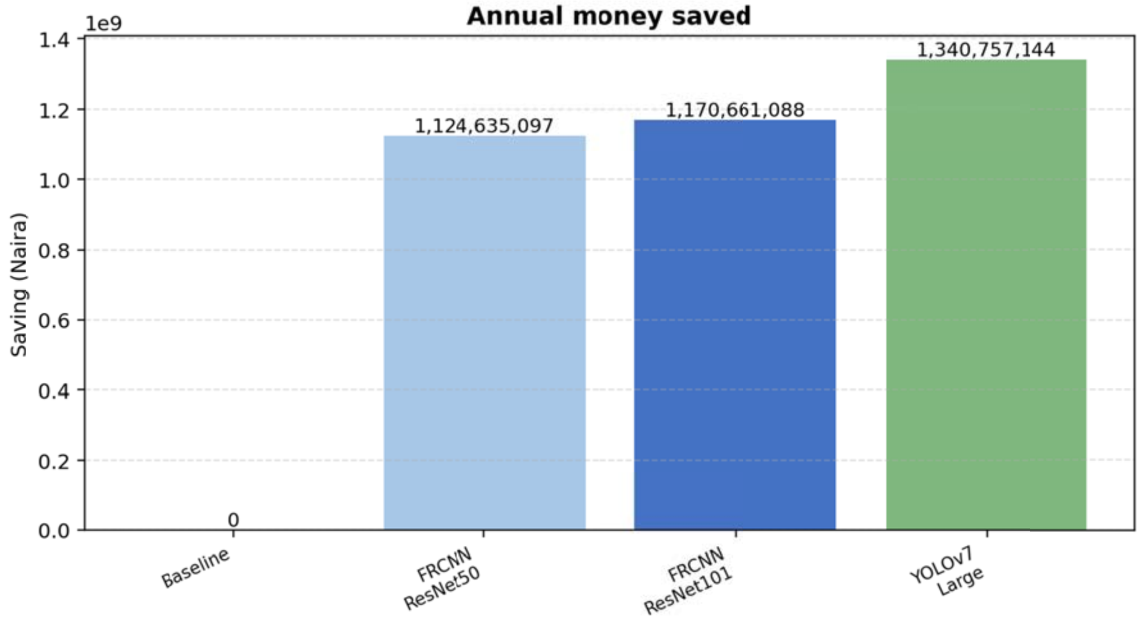

Figure 15. Comparison of annual money saved for base-station models.

3.7 Overall comparison with onboard models

Tables 7 and 8 are included to place the base-station results within the wider thesis evaluation. They are not the primary basis for selecting the best base-station model because onboard and base-station models operate under different computing, energy, and latency conditions.

Table 7. Normalized amount of money saved annually for implementing bird pest control.

Model	Normalized amount of money saved annually (%)	Rank
Base Station: Faster R-CNN (ResNet50)	83.88%	6
Base Station: Faster R-CNN (ResNet101)	87.31%	5
Base Station: YOLOv7-Large	100.00%	1
Onboard: MobileNetV3-SSD	89.80%	4
Onboard: EfficientDet-Lite	91.07%	3
Onboard: YOLOv5-Nano	92.77%	2

Table 8. Combined model performance ranking across base-station and onboard models.

Model	Normalized early warning accuracy (%)	Normalized throughput (%)	Combined model performance (%)	Rank
Base Station: Faster R-CNN with ResNet50 Backbone	68.89%	15.59%	42.24%	5
Base Station: Faster R-CNN with ResNet101 Backbone	88.89%	0.00%	44.45%	4
Base Station: YOLOv7-Large	100.00%	37.54%	68.77%	1
Onboard: MobileNetV3-SSD	0.00%	35.89%	17.95%	6
Onboard: EfficientDet-	22.22%	59.14%	40.68%	3

Model	Normalized early warning accuracy (%)	Normalized throughput (%)	Combined model performance (%)	Rank
Lite				
Onboard: YOLOv5-Nano	48.89%	100.00%	74.45%	2

3.8 Discussion of findings

The results show that model selection for a drone-based bird pest deterrent system should consider both technical and economic performance. Faster R-CNN with ResNet101 improves accuracy compared with ResNet50, but its higher latency reduces its practical attractiveness for fast response. YOLOv7-Large gives the best base-station balance because it has the lowest pipeline latency, the lowest time-to-detection, the highest early warning accuracy, and the highest CEF.

The economic interpretation is also important. The estimated baseline annual financial loss of 1.54 billion Naira shows that bird pest damage is economically significant enough to justify technology-assisted intervention. Faster R-CNN with ResNet101 reduces this loss by about 1.17 billion Naira per year, while YOLOv7-Large reduces it by about 1.34 billion Naira per year. This indicates that the model with the strongest technical performance also provides the highest estimated economic benefit.

The base-station approach is most suitable where the communication link between the drone and the base station is reliable and has low latency. It also requires stable power, a rugged computing unit, a farm-side communication gateway, and a clear operational plan for sending drone frames to the base station and returning commands to the drone. The onboard approach is more suitable where the communication link is weak or where immediate local inference is required. A practical deployment may combine both approaches. The onboard model can provide immediate detection and fallback response, while the base station can provide more accurate validation, logging, retraining, and decision support.

4. Conclusion

This paper presented an evaluation of base-station deep learning models for drone-based bird pest monitoring and deterrence in rice farms. The study examined the reported technical and economic outcomes and linked them to practical rice-loss reduction. The system model shows how a drone camera, wireless link, base-station AI unit, tracking module, and deterrent decision stage can work together to reduce bird-related rice loss.

The results show that YOLOv7-Large is the best base-station model. It records an end-to-end latency of 74.50 ms, time-to-detection of 187.33 ms, early warning accuracy of 94.0%, and CEF of 0.87. In financial terms, it reduces annual rice loss from 644.04 tons to 83.64 tons and reduces the cost of rice lost from 1,540,870,150.05 Naira to 200,113,006.50 Naira. This gives an annual saving of 1,340,757,143.55 Naira.

Future work should implement the system on a physical drone and base-station prototype, test it under real rice field conditions, measure wireless communication delay, and validate rice loss reduction over multiple planting seasons. More Nigerian rice-farm drone images should also be collected to improve local model adaptation and strengthen pest-species classification. The study therefore shows that base-station AI processing can provide a practical decision-support layer for drone-based bird pest deterrence when reliable communication, adequate computing support, and timely response are available.

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