proceedings

Enhanced Drone Detection Model for Edge Devices Using Knowledge Distillation And Bayesian Optimization

MDPI

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Problem

- The proliferation of drones (UAVs) raises significant concerns regarding security and privacy.
- Deploying drone detection models on edge devices is challenging due to resource constraints that hinder the feasibility of complex deep learning models.
- Knowledge distillation effectively compresses neural networks for UAV detection in constrained environments, but optimizing its hyper parameters is challenging due to the vast and complex search space.

Contribution

- The study introduces the LDDm-CNN model, a lightweight Convolutional Neural Network (CNN) designed to detect drones efficiently on resource constrained devices.
- One of the key innovations in this research is the proposal of Bayesian optimization- based knowledge distillation.

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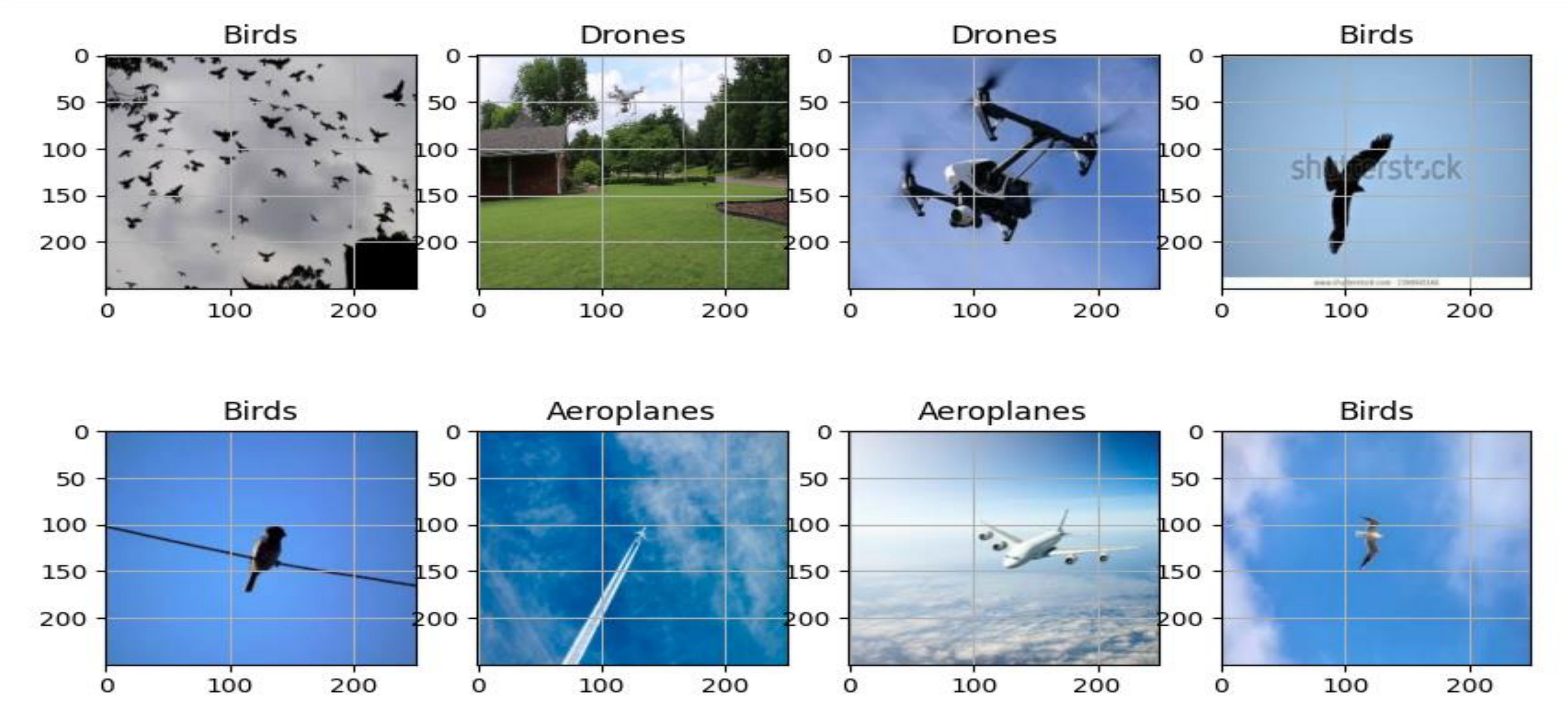
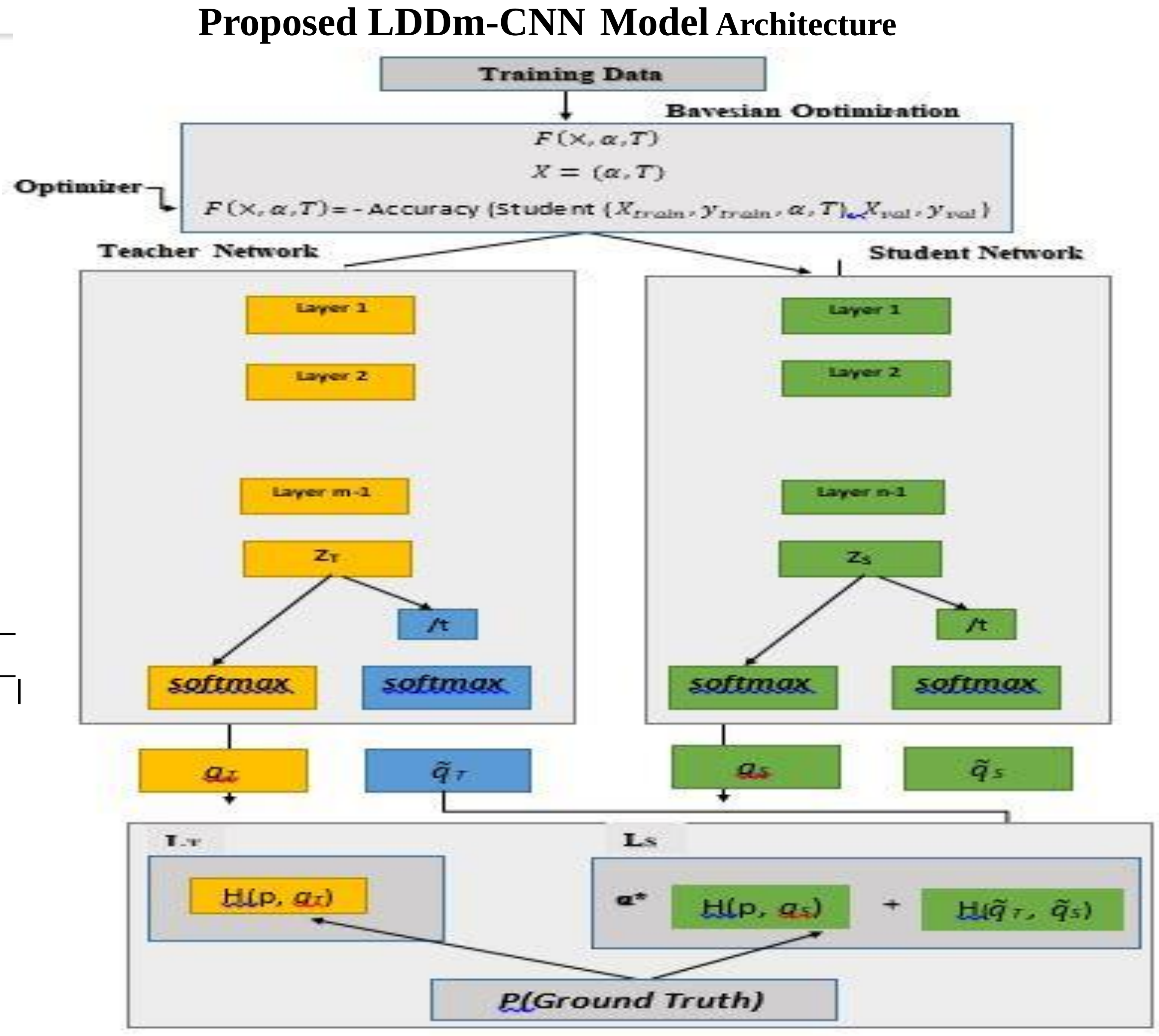
Method

Sample Images From The Dataset



Proposed LDDm-CNN Model Architecture



The Training Process

Algorithm2 : Proposed LDDm-CNN Model Algorithm

Input: Teacher model, (T_opt, α_opt, from Bayesian optimization)

Output: LDDm-CNN Model

1. Initialize T_model (Teacher model), S_model (Student model), Opt_T , X_Train,Y_Train X_val, Y_val and S_loss (Student Loss), D_loss (Distillation Loss), G_loss (General Loss),
2. Define Bayesian optimization

$$F(\times : \alpha, T)$$

$$X = (\alpha, T)$$

Where:
α, T: are the hyper-parameters to be optimzed

f(x: α, T)=Accuracy (Student (X_train, Y_train, α, T) X_val, Y_val,)

3. Train teacher model to obtain soft labels of teacher model using scaled softmax with (T_opt, α_opt, from Bayesian optimization)

$$Softmax_{scaled}(Z_i) = \frac{e^{Z_i/T\_opt}}{\sum_j e^{Z_i/T\_opt}}$$

4. Train student model to compute the general loss using distilled knowledge obtain from above teacher model:

Student model phase 1 to find student loss:

$$S_{loss} = \alpha \cdot SoftmaxLoss(Z_{student}, soft\_labels)$$

Student model phase 2 to find Distillation loss:

$$D_{loss} = (1-\alpha) \cdot CE(Z_{student}, hard\_labels)$$

5. General loss Function:

$$General_{Loss} = \alpha \cdot SoftmaxLoss(Z_{student}, soft\_labels) + (1-\alpha).CE(Z_{student}, hard\_labels)$$

6. Minimize general loss on the ground Truth
7. Stop

- The proposed LDDm-CNN Model combines the strengths of knowledge distillation and Bayesian optimization, as illustrated in Figure above, to achieve accurate drone detection with efficient, resource-constrained models.
- Knowledge distillation compresses large, pre-trained teacher models into smaller, faster student models while preserving their accuracy, allowing for deployment on edge devices.
- Meanwhile, Bayesian optimization efficiently searches a vast hyper parameter space to identify the configuration that optimizes the knowledge distillation process, ensuring the student model achieves peak performance in drone detection.

Result

Table 1: Performance of the Proposed LDDm-CNN Model

Models	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)	Model size	Training time	No.params
Proposed model	0.89	0.90	0.89	0.95	5.63 MB	10 min	1,477,123
Baseline Model	0.70	0.74	0.73	0.74	281.35 MB	14 min	73,755,403

Table 4.2: Comparison of the Proposed LDDm-CNN Model with Bigger Models

Models	Accuracy (%)	Recall (%)	Precision (%)	Size	No.params	Training-time
K S Bhavishya et. al.	0.955	0.91	0.96	-	-	-
F Mahdavi et al. (2020)	0.95	-	-	-	-	-
S. S. Alam *et al.*	0.975	0.980	0.980	-	-	-
Proposed model	0.95	0.90	0.89	5.63 MB	1,477,123	10min

- Compared to existing drone detection models in Table 2, the proposed LDDm-CNN excelled in size, training time, and real-time inference, despite being smaller and simpler.
- This demonstrates the effectiveness of knowledge distillation hyper parameter optimization using Bayesian optimization in building efficient, lightweight models.

Conclusion

In this study, we introduces the LDDm-CNN, a lightweight drone detection model specifically designed for resource-constrained environments. This model leverages a shallow Convolutional Neural Network (CNN) architecture, optimized for efficiency, making it suitable for real-time detection on edge devices with limited computational resources.