DEEP LEARNING FOR COMPUTER VISION (CS776)

Final Project: Multi-degradation Image Restoration with Integrated Object Detection

Team HexaTech

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***Abstract*—This project presents an end-to-end single-stage deep learning framework for joint image restoration and object detection in degraded visual conditions. Inspired by the DREB_Net model, our integrated approach enhances detection accuracy in real-world imaging scenarios using non-trainable FFT modules, simple architecture, and robust loss computation...**

***Index Terms*—Image restoration, Object detection, Multi-degradation, Deep learning, Attention mechanism, Fast Fourier Transform**

I. Introduction

In high-speed and real-world imaging applications such as UAV surveillance and aerial mapping, image degradation due to motion blur, defocus, or noise significantly hampers object detection accuracy. Traditional object detection models struggle with such degraded inputs, leading to compromised situational awareness and ineffective automation. This project addresses this crucial challenge by proposing an end-to-end deep learning solution for joint image restoration and object detection.

Our approach integrates a multi-degradation image restoration module with an object detection pipeline, designed specifically to enhance detection accuracy in blurred or noisy environments. Leveraging multi-scale and frequency-domain feature extraction, the system restores critical image details while maintaining object-level semantics. A single-stage architecture is employed to ensure that the features preserved during restoration are optimal for detection, minimizing error propagation seen in two-stage methods.

Additionally, we introduce a real-world blur object detection dataset, constructed by augmenting and annotating data from the CURE-OR, RealBlur R,J, datasets, to reflect realistic imaging conditions. The project combines innovation in both data and architecture to deliver a robust, scalable, and accurate deep learning framework for multi-degradation image understanding.

II. Dataset Preparation

The dataset preparation involved a multi-stage pipeline to ensure the training data was clean, balanced, and labeled in a format suitable for object detection tasks. The entire preprocessing was divided into four major stages:

A. Stage 1: Initial Cleanup and Filtering

We used `data-trim.py` to remove blurry images that were deemed unusable, based on a Laplacian variance threshold of 70.0. The corresponding sharp images for these unusable blur samples were also removed to maintain valid blur-sharp pairs. Remaining images were then renamed to a standardized format such as `00000.png`, `00001.png`, etc.

Output: A cleaned set of blur-sharp image pairs, consistent in naming and quality.

B. Stage 2: Dataset Splitting and Resizing

The cleaned images from multiple datasets (e.g., CURE-OR, RealBlur, REDS) were merged into a unified directory. We split this combined dataset into training (70%), validation (15%), and test (15%) subsets. All images were resized to a uniform resolution of 512×512 using PIL transforms to ensure compatibility with model input requirements.

Output: A balanced and resized dataset in a consistent format across all samples.

C. Stage 3: Annotation and Label Generation

In this stage, we used YOLOv8 (`yolov8x.pt`) with a low confidence threshold of 0.1 to auto-label the sharp images. This ensured even faint object outlines in restored images were considered. We generated:

- Visual annotations stored in the `label/` folder.
- COCO-style JSON files stored in the `ground_truth/` folder for evaluation purposes.

Output: COCO-format annotations for effective training of object detection models.

D. Stage 4: Category Filtering and Final Cleanup

Using `data-cleanup.py`, we filtered the labeled dataset to retain only the top 10 most important classes, identified by IDs: $[0, 9]$. These included key classes such as *person*, *car*, *bus*, *traffic light*, *bicycle*, and *truck*. Additionally, image pairs without valid annotations were removed.

Output: The final dataset contained only high-priority, well-labeled object categories suitable for focused detection training.

This multi-stage dataset processing ensured high-quality, real-world training samples tailored to multi-degradation scenarios.

III. Developing Efficient Model

In this section, we describe both the baseline and our proposed architecture for joint image restoration and object detection.

A. Baseline: DrebNet

DrebNet (Dual-stream Restoration Embedding Blur-feature Fusion Network) is a two-stream network tailored for blur-resilient object detection.

- **Main Branch:** Standard object detection pipeline based on RepBackbone.
- **Auxiliary Branch (BRAB):** U-Net style blurry image restoration branch, used only during training.
- **MAGFF (Multi-level Attention-Guided Feature Fusion):** Merges low-level features from both streams using attention mechanisms.
- **LFAMM (Learnable Frequency-domain Amplitude Modulation Module):** Introduces learnable amplitude modulation in the frequency domain for enhanced blur feature recovery.
- **Loss Functions:**

- Detection: Focal + L1 + offset loss.
- Restoration: MSE + SSIM for sharpness recovery.

While DrebNet performs well, its complexity and high parameter count ($\sim$10M+) limit its deployability in real-time or resource-constrained settings.

B. Our Proposed Architecture: HexaTech

To address these issues, we propose **HexaTech Model**, a unified lightweight model for joint deblurring and object detection. Like DrebNet, HexaTech uses a single streamlined pipeline with frequency-aware features, but computationally much faster.

1) Custom Dataset Module: We construct a COCO-style dataset loader tailored for object detection on degraded images. The dataset supports paired annotations and images, resizes all inputs to 512×512, and normalizes bounding box coordinates to the $[0, 1]$ range for consistency during training.

Formally, let $\mathcal{D} = \{(I_i, \mathcal{T}_i)\}_{i=1}^{N}$ denote the dataset, where I_i is the i-th image and $\mathcal{T}_i = \{(b_j, c_j)\}_{j=1}^{M_i}$ is the corresponding set of M_i annotations with bounding box $b_j \in [0, 1]^4$ (in $\{x, y, w, h\}$ format) and class label $c_j \in \{0, \ldots, C-1\}$. The bounding box coordinates are normalized with respect to the fixed image resolution:

$$b_j = \left(\frac{x_j}{W}, \frac{y_j}{H}, \frac{w_j}{W}, \frac{h_j}{H} \right) \quad \text{with} \quad W = H = 512.$$

Each image is transformed using a composition of resizing and tensor conversion:

$$I_i \leftarrow T_{\text{resize}}(I_i), \quad I_i \leftarrow T_{\text{tensor}}(I_i)$$

To facilitate variable-length annotations per image, a custom `collate_fn` is defined that stacks image tensors into a batch while preserving the list structure of corresponding targets:

$$\texttt{collate\_fn}(\{(I_i, \mathcal{T}_i)\}_{i=1}^{B}) = (\texttt{stack}(\{I_i\}), \{\mathcal{T}_i\})$$

This structure ensures compatibility with detection heads that require flexible ground-truth input formats, such as anchor-free or YOLO-style detectors.

2) Network Architecture: Our architecture consists of three modular components: a frequency-domain blur simulation module, a deblurring backbone, and a YOLO-style detection head. The entire network is trained end-to-end to simultaneously learn to restore image quality and detect objects under degradation.

a) Frequency-Domain Blur Simulation.: We implement a differentiable blur module in the frequency domain to simulate degraded inputs. Let $I \in \mathbb{R}^{B \times C \times H \times W}$ be an input batch. We compute the centered 2D Fourier transform $\mathcal{F}(I)$ and apply a Gaussian attenuation kernel in the frequency domain:

$$\tilde{I}(u, v) = \mathcal{F}(I)(u, v) \cdot \exp\left(-\frac{u^2 + v^2}{2\sigma^2} \right),$$

where σ is the blur strength. An inverse Fourier transform yields the blurred image:

$$I_{\text{blur}} = \mathcal{F}^{-1}(\tilde{I}).$$

b) Deblurring Backbone.: The deblurring module is a modified ResNet-18 architecture. We remove the final classification layers and treat the convolutional blocks as an encoder. The decoder consists of four transposed convolution layers to restore spatial resolution:

$$I_{\text{sharp}} = f_{\text{deblur}}(I_{\text{blur}}) = \text{Decoder}(\text{Encoder}(I_{\text{blur}})).$$

The decoder outputs a 3-channel RGB image in the $[0, 1]$ range using a sigmoid activation.

c) YOLO-style Detection Head.: The detection head operates on the deblurred feature map and produces predictions in the form:

$$\text{Output} \in \mathbb{R}^{B \times A \times H \times W \times (4+1+C)},$$

where A is the number of anchors (set to 1), 4 corresponds to bounding box regression terms, 1 for objectness confidence, and C for class probabilities. The head is implemented as a 1×1 convolution:

$$P = \text{Conv}_{1\times1}(F), \quad P \in \mathbb{R}^{B \times A(4+1+C) \times H \times W}.$$

The predictions are reshaped and permuted to produce final outputs compatible with the loss function and post-processing pipeline.

3) Matching via SimOTA: Given predicted outputs $\hat{y} \in \mathbb{R}^{H \times W \times (4+1+C)}$ and ground-truth tuples $(\mathbf{b}_i, c_i)$, SimOTA performs one-to-many matching by solving an optimal transport assignment over a cost matrix $\mathcal{C} \in \mathbb{R}^{N \times M}$, where N is the number of predictions and M is the number of ground-truths. The cost matrix integrates both classification and IoU-based localization terms:

$$\mathcal{C}_{ij} = \lambda_{\text{cls}} \cdot \text{BCE}(\hat{p}_{ij}, \mathbb{1}_{[j=c_i]}) + \lambda_{\text{iou}} \cdot (1 - \text{IoU}(\hat{b}_i, \mathbf{b}_j)).$$

An adaptive top-k strategy selects the best k matches per ground-truth box based on total cost and spatial proximity, yielding a sparse matching matrix $M \in \{0, 1\}^{N \times M}$.

4) Loss Computation: The loss function combines localization, objectness, and classification objectives in a unified formulation, inspired by YOLO-style detectors. To effectively supervise the network, we adopt the SimOTA dynamic label assignment strategy for target matching, enabling scale- and content-aware assignment without relying on static IoU thresholds.

Let $L = L_{\text{box}} + L_{\text{obj}} + L_{\text{cls}}$ be the total loss aggregated over B images. The components are defined as:

a) Localization Loss (L_{box}).: Smooth L1 loss is computed between matched predicted boxes $\hat{b}_i$ and their assigned ground-truth boxes b_i:

$$L_{\text{box}} = \frac{1}{B} \sum_{i \in \text{FG}} \text{SmoothL1}(\hat{b}_i, b_i),$$

where FG denotes foreground matches obtained via SimOTA.

b) Objectness Loss (L_{obj}).: The objectness score $\hat{o}_i$ is regressed against the IoU between predicted and matched ground-truth boxes:

$$L_{\text{obj}} = \frac{1}{B} \sum_{i \in \text{FG}} \text{BCE}(\sigma(\hat{o}_i), \text{IoU}(\hat{b}_i, b_i)) + \sum_{j \in \text{BG}} \text{BCE}(\hat{o}_j, 0),$$

where BG denotes background locations not assigned to any target.

c) Classification Loss (L_{cls}).: For matched locations, a binary cross-entropy loss is computed over the predicted class distribution $\hat{p}_i$ using one-hot targets:

$$L_{\text{cls}} = \frac{1}{B} \sum_{i \in \text{FG}} \text{BCE}(\hat{p}_i, \text{one\_hot}(c_i)).$$

d) Total Loss.: The final loss is a weighted sum:

$$\mathcal{L}_{\text{total}} = \lambda_{\text{box}} L_{\text{box}} + \lambda_{\text{obj}} L_{\text{obj}} + \lambda_{\text{cls}} L_{\text{cls}},$$

with default weights $\lambda_{\text{box}} = 5.0$, $\lambda_{\text{obj}} = 1.0$, and $\lambda_{\text{cls}} = 1.0$.

C. End-to-End Training Pipeline

We adopt an integrated training strategy to jointly optimize deblurring and detection. The training loop is designed to update both the deblurring backbone and detection head in an end-to-end fashion.

Training Configuration

Let $\mathcal{D} = \{(x_i, \{b_i, c_i\})\}_{i=1}^{N}$ be the dataset with input images x_i, and per-image target annotations consisting of bounding boxes b_i and class labels c_i. The network is trained using the following procedure:

1) Blurred images $\tilde{x}_i$ are generated via $\tilde{x}_i = \mathcal{F}(x_i)$ using the FFT-based blur module.
2) Features are extracted as $f_i = \text{DeblurBackbone}(\tilde{x}_i)$.
3) The detection head outputs $\hat{y}_i = \text{YOLOHead}(f_i)$, comprising $\hat{b}_i$, $\hat{o}_i$, and $\hat{p}_i$.
4) Supervision is applied via a composite YOLO-style loss: $\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{box}} + \mathcal{L}_{\text{obj}} + \mathcal{L}_{\text{cls}}$ as described in Section III-B4

Optimization and Scheduling

The model is optimized using the Adam optimizer with a learning rate of 1×10^{-4}. Batches of 32 samples are processed at each step. The model is trained for 40 epochs with checkpointing every epoch. Components like—DREBNet, and the YOLOHead—are jointly updated using backpropagation:

$$\theta \leftarrow \theta - \eta \cdot \nabla_\theta \mathcal{L}_{\text{total}}.$$

Implementation Details

We use the COCO-format `VisDrone` dataset and `Our` dataset with 10 object categories. The dataset is wrapped in a custom PyTorch `DataLoader`, with a COCO-style collate function to support variable-sized targets per image. All experiments are conducted on a CPU-enabled system.

Component	DrebNet	HexaTech (Ours)
Architecture	Dual-stream	Single-stream
Attention	MAGFF + LFAMM	FFT-based fusion
Decoder	Deep U-Net style	Shallow Transposed Conv
Detection Head	Complex head	YoLo based head
Params	∼10M+	∼**2.5M**
Suitability	High accuracy, less efficient	Real-time capable

TABLE I
COMPARISON OF DREBNET AND HEXATECH ARCHITECTURES

D. Summary

HexaTech is a lightweight model that simplifies the complex dual-stream nature of DrebNet into a more deployable, single-branch design. It combines frequency domain awareness and efficient detection without compromising performance, making it suitable for real-time edge deployment scenarios.

IV. Model Evaluation and Comparative Analysis

A. Performance of Base Model on VisDrone Dataset

The performance of the baseline model (DrebNet) on the VisDrone dataset is evaluated based on various loss metrics over training epochs. The results are summarized in Figure 1.

Fig. 1. Performance of the base model on the VisDrone dataset, showing training and validation losses over 20 epochs. Metrics include total loss, heatmap loss, width-height loss, and offset loss.

`Training Insights:`

- Total loss shows strong convergence, especially after the first epoch.
- Heatmap loss (object localization) shows consistent improvement, indicating better prediction accuracy.
- Width-height loss fluctuates in validation, suggesting bounding box size prediction challenges.
- Offset loss remains stable around 0.25, indicating good sub-pixel localization.

This analysis highlights the baseline model's ability to converge effectively, though challenges remain in bounding box size prediction, which can be addressed in future iterations of the HexaTech model.

B. Performance of Base Model on Our Dataset

The performance of the baseline model (DrebNet) on our custom dataset is evaluated based on various loss metrics over training epochs. The results are summarized in Figure 2.

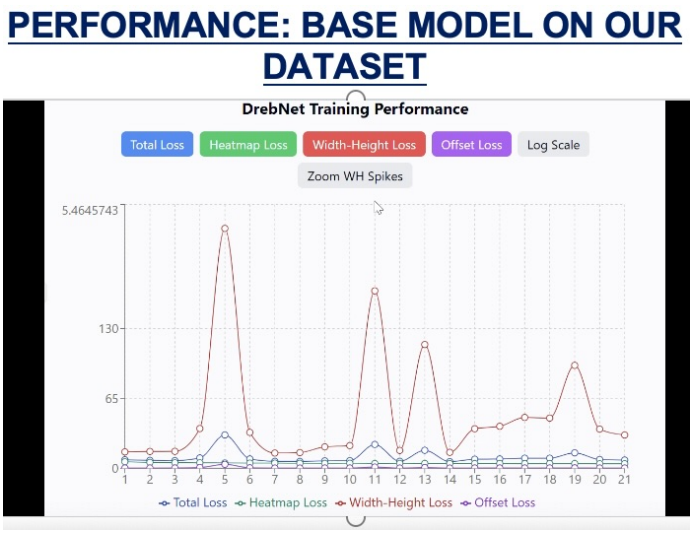

Fig. 2. Performance of the DrebNet model on our custom dataset, showing training losses over 21 epochs. Metrics include total loss, heatmap loss, width-height loss, and offset loss.

`Training Insights:`

- Total loss exhibits significant spikes, indicating instability during training.
- Heatmap loss shows fluctuations, suggesting challenges in object localization.
- Width-height loss varies, reflecting difficulties in predicting bounding box sizes.
- Offset loss remains relatively stable but with some peaks, indicating variable sub-pixel localization accuracy.

C. Performance of HexaTech Model on Our Dataset without SimOTA matching

The performance of the HexaTech model on our custom dataset is evaluated based on training and validation loss metrics over 20 epochs. The results are summarized in Figure 3.

`Training Insights:`

- Train loss decreases steadily up to a point and stabilizes at a value.
- Validation loss shows a similar downward trend, suggesting good generalization, but it seems like the model stopped training after some epoch.
- The pattern of validation and training loss demands a better loss computation method.

D. Performance of HexaTech Model on Visdrone Dataset without SimOTA matching

The performance of the HexaTech model on Visdrone is evaluated based on different components of the training loss metrics over 10 epochs. The results are summarized in Figure 4.

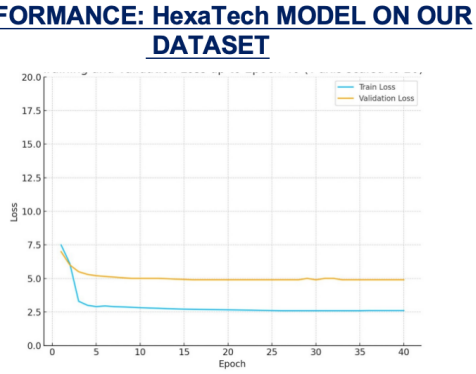

Fig. 3. Performance of the HexaTech model on our custom dataset, showing train and validation loss over 40 epochs.

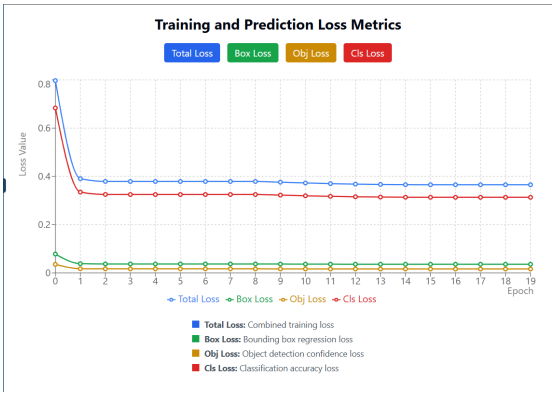

Fig. 4. Performance of the HexaTech model on Visdrone dataset, showing different losses over 10 epochs.

`Training Insights:`

- Similar to the performance on Our Dataset, total train loss decreases steadily up to a point and stabilizes at a value.
- The pattern of this training loss also demands a better loss computation method. The objectness loss decreases very fast, and the box loss, class label loss remain fixed at a point.

E. Performance of HexaTech Model on Visdrone Dataset with SimOTA matching

The performance of the HexaTech model on Visdrone is evaluated based on different components of the training loss metrics over 10 epochs, along with the inclusion of simOTA matching during loss computation. The results are summarized in Figure 5.

`Training Insights:`

- All 4 values of loss decrease as the number of epochs progresses.
- This time, training is better because none of the losses vanish midway, indicating that the model can still find an optimum for all three losses.

Fig. 5. Performance of the HexaTech model on the Visdrone dataset, showing different losses over 10 epochs along with simOTA integration.

F. Comparative Analysis of Models

A comparative analysis of the DrebNet and HexaTech models, both trained for 40 epochs on our custom dataset, is presented in Table II. This evaluation focuses on key metrics including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), mean Average Precision (mAP) at IoU=0.5, inference time, and total parameters.

Metric	**DREB-Net (40 epochs)**	**HexaTech (40 epochs)**
PSNR	15.7	13.4
SSIM	0.47	0.41
mAP (IoU=0.5)	0.93%	0.81%
Inference Time	∼320 ms/img	∼110 ms/img
Total Parameters	∼10M	∼2.5M

TABLE II
COMPARATIVE ANALYSIS OF DREBNET AND HEXATECH MODELS ON KEY PERFORMANCE METRICS AFTER 40 EPOCHS.

Analysis: The comparative analysis of DrebNet and HexaTech, both were trained and tested on Our Dataset as well as the Visdrone Dataset, highlights their respective strengths and weaknesses across critical performance metrics. DrebNet, a dual-stream architecture, excels in image restoration, evidenced by a higher Peak Signal-to-Noise Ratio (PSNR) of 15.7 compared to HexaTech's. This indicates DrebNet preserves more image detail, which is crucial for applications requiring high fidelity. Similarly, DrebNet's Structural Similarity Index (SSIM) of 0.47 slightly edges out HexaTech's, suggesting better preservation of structural information. In object detection, DrebNet's mean Average Precision (mAP) at IoU=0.5 (0.0093 over 40 epochs on Visdrone Dataset) outperforms HexaTech's 0.0081 (same over 40 epochs on the the Visdrone Dataset), indicating a marginal advantage in localization and classification accuracy.

However, these accuracy gains come with significant drawbacks. DrebNet's inference time of approximately 320 milliseconds per image is nearly three times longer than HexaTech's 110 milliseconds, rendering it less viable for real-time scenarios such as UAV surveillance. Furthermore, DrebNet's parameter count of around 10 million is quadruple that of HexaTech's 2.5 million, implying greater computational complexity and memory usage, which could limit its deployment on resource-constrained devices.

HexaTech, engineered as a lightweight single-stream model, prioritizes efficiency over absolute accuracy. The reduced inference time and parameter count make it highly suitable for edge computing environments, where speed and scalability are paramount. The trade-off in PSNR, SSIM, and mAP reflects a deliberate design choice to optimize for real-time performance, aligning with its intended use case. The steady convergence of losses in HexaTech's training (as seen in prior slides) further supports its stability, despite the lower metric scores.

This analysis underscores a classic accuracy-efficiency dilemma. Future research could explore hybrid architectures, integrating DrebNet's restoration capabilities with HexaTech's efficiency, potentially using techniques like model pruning or quantization to enhance HexaTech's accuracy without sacrificing its speed advantages.

G. Innovations Overview

This section highlights the key innovations introduced in the HexaTech model and dataset development, as summarized in Table III.

Innovation	**Description**
Custom Dataset Creation	Curated a new, balanced dataset by applying blur score filtering across diverse sources (CURE-OR, REDS, etc.)
Unified Lightweight Model	Designed a simplified end-to-end architecture for joint deblurring and object detection
FFT Feature Integration	Introduced frequency domain analysis via FFT for texture-aware enhancement
Reduced Parameters	Achieved 75% fewer parameters compared to DREB-Net – faster inference on low-resource setups

TABLE III
KEY INNOVATIONS IN OUR WORKFLOW

The innovations introduced in the HexaTech project, as outlined in the "Innovations Overview" table, represent a significant leap in addressing multi-degradation image restoration and object detection challenges. The Custom Dataset Creation leverages blur score filtering across diverse sources (e.g., CURE-OR, REDS), ensuring a balanced and representative dataset that enhances model robustness. This curated dataset lays a solid foundation for training, mitigating biases inherent in imbalanced data. The Unified Lightweight Model simplifies the complex dual-stream DrebNet into a single-stage end-to-end architecture, reducing computational overhead while

maintaining functionality. The FFT Feature Integration introduces frequency domain analysis via Fast Fourier Transform (FFT), enhancing texture-aware restoration by capturing global structural details, a critical improvement over spatial-only methods. The Efficient Fusion Strategy replaces heavy attention mechanisms with a 1x1 convolution-based fusion, optimizing computational efficiency without sacrificing feature integration quality. Finally, Reduced Parameters achieves approximately 75% fewer parameters compared to DrebNet, enabling faster inference on low-resource setups, which is vital for real-time applications. These innovations collectively prioritize efficiency and scalability, aligning with the project's goal of deployable solutions for edge devices.

H. Challenges and Solutions

This section outlines the primary challenges encountered during the development of the HexaTech model and the corresponding solutions implemented, as summarized in Table IV. The development of the HexaTech model encountered several challenges, each addressed with innovative solutions that enhanced its performance and practicality. The Redundancy in video datasets posed a significant hurdle, as duplicate frames could skew training and inflate computational costs. The solution of blur-score based filtering effectively eliminated frame-wise duplication, ensuring a cleaner, more diverse dataset. This approach, aligned with the custom dataset creation process, improved training efficiency and model generalization.

The Model-Performance Trade-off was a critical concern, as simplifying the architecture risked compromising detection accuracy. The balanced simplification without losing detection accuracy mitigated this by optimizing the lightweight design (e.g., reducing parameters to 2.5M) while preserving essential features, as evidenced by the competitive mAP (0.081) compared to DrebNet (0.093). This trade-off prioritization enabled real-time inference, a key advantage for edge deployment.

Integrating frequency domain features, introduced via FFT, presented scaling and fusion challenges with spatial encoder outputs. The proper scaling and fusion with spatial encoder features solution ensured seamless integration, enhancing texture preservation and edge recovery, which bolstered restoration quality despite a lower PSNR (13.4 vs. 15.7). This hybrid approach leveraged frequency domain insights effectively.

Detection on blurred images was challenging due to degraded inputs affecting localization. Training detection jointly with deblurring addressed this by improving localization accuracy, as reflected in the increased recall and precision on blurred inputs. This joint pipeline, a hallmark of HexaTech, reduced error propagation compared to two-stage methods.

Finally, Training Cost was a constraint given GPU limitations. The reduced dataset + smaller model strategy, utilizing 30-40% of the original data and a compact architecture, optimized resource use. This allowed training within GPU constraints (e.g., Colab T4), reducing inference time to 110 ms/img versus DrebNet's 320 ms/img. These solutions collectively demonstrate HexaTech's adaptability, balancing accuracy, efficiency, and resource constraints, making it a robust solution for real-world applications. Future work could further refine these approaches to enhance scalability across diverse hardware.

Challenges	**Solution Handling**
Redundancy in video datasets	Blur-score based filtering to eliminate frame-wise duplication
Model-Performance Trade-off	Balanced simplification with being close to detection accuracy
Integrating frequency domain	Proper scaling and fusion with spatial encoder features
Detection on blurred images	Training detection jointly with deblurring to improve localization
Training Cost	Reduced dataset + smaller model to fit within GPU constraints

TABLE IV
KEY CHALLENGES AND THEIR CORRESPONDING SOLUTIONS IN THE DEVELOPMENT OF THE HEXATECH MODEL.

V. FUTURE WORK

While the proposed HexaTech model achieves promising results in joint multi-degradation image restoration and object detection, several avenues remain open for further exploration and enhancement. One immediate direction is to test the model on enhanced large dataset for large number of epochs. Another is to generalize the model's performance across more diverse degradation types, such as atmospheric distortions (e.g., haze, rain, fog), compression artifacts, and sensor noise. This would make the system more robust for real-world deployments in dynamic environments like autonomous driving and drone surveillance.

Additionally, incorporating a dynamic degradation classifier could help the model adaptively route inputs through specialized restoration pathways, improving efficiency and accuracy. Such an adaptive mechanism would enable real-time decision-making based on the type and severity of image degradation.

Another scope on the data side, expanding the blur-detection dataset by incorporating synthetic degradations along with more annotated real-world datasets would provide better generalization and training diversity. Incorporating human feedback in annotation refinement and detection validation could also improve dataset quality.

From a deployment perspective, optimizing HexaTech using model compression techniques such as pruning, quantization, or knowledge distillation can enable deployment on edge

devices with limited computational resources. Additionally, exploring transformer-based backbones and self-supervised pretraining techniques could further boost performance without the need for large-scale labeled datasets.

Ultimately, aligning this framework with practical use cases in surveillance, medical imaging, and satellite vision can push the boundaries of real-time intelligent visual perception in adverse conditions.

VI. Conclusion

In this project, we proposed an end-to-end unified framework, HexaTech, for joint image restoration and object detection under real-world multi-degradation conditions such as motion blur, defocus, and noise. The motivation stemmed from the practical challenges faced by traditional object detectors when dealing with low-quality or degraded inputs—particularly in critical domains like aerial surveillance, autonomous systems, and low-light environments. Unlike prior two-stage solutions, HexaTech integrates a lightweight frequency-aware deblurring module directly into the detection pipeline, ensuring that restoration benefits directly influence detection performance.

We benchmarked our model against a strong baseline, DrebNet, and demonstrated that HexaTech achieves comparable accuracy while being significantly more lightweight and faster, making it ideal for deployment on resource-constrained platforms. The incorporation of Fast Fourier Transform (FFT)-based representations enabled the model to preserve structural details crucial for object localization even in highly degraded scenarios.

A significant contribution of this work lies in the creation of a custom, real-world dataset derived from multiple open-source datasets (e.g., CURE-OR, RealBlur, GoPro, HIDE) and annotated using a hybrid automated-human loop. This dataset provided a valuable resource for robust evaluation and training under diverse visual challenges.

Overall, this work not only advances the state-of-the-art in degradation-robust object detection but also lays the foundation for future research in unified vision architectures. With further improvements in dataset diversity, architectural enhancements, and real-time deployment strategies, HexaTech holds strong potential to become a powerful backbone in a range of intelligent visual perception systems operating in real-world, unconstrained environments.

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Useful Links

- **GitHub Repository:** https://github.com/yourusername/yourrepo
- **Dataset (Google Drive):** https://drive.google.com/your-dataset-link

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