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Review

Image processing techniques for detection of objects in blurry pictures: A comprehensive review

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Abstract: Detecting objects in blurry and degraded images remains a critical unsolved challenge in computer vision, affecting applications from medical diagnostics and autonomous navigation to remote sensing and surveillance. Image degradation caused by motion, defocus, poor lighting, or environmental factors severely compromises feature visibility and limits the performance of conventional detection algorithms. This paper presents a comprehensive, systematic review of state-of-the-art techniques designed to address this problem. We first categorize common image degradations and analyze classical and deep learning-based solutions for image deblurring and enhancement, including CNN (Convolutional Neural Networks), GAN (Generative Adversarial Networks), and transformer architectures. The review then critically examines object detection models, particularly YOLO (You Only Look Once) and CNN-based networks, adapted for low-quality inputs. A key focus is on integrated pipelines that jointly optimize restoration and detection. We synthesize findings from over 200 studies, highlighting performance across diverse domains such as UAV (Unmanned Aerial Vehicle) imagery, underwater exploration, and medical analysis. Furthermore, we discuss standard datasets and evaluation metrics, identify persistent challenges including real-time processing, multi-degradation handling, and domain adaptation, and outline promising research directions. This review serves as a foundational resource for researchers and practitioners aiming to build robust vision systems for real-world, blur-prone environments.

Keywords: blurry image processing; image deblurring; object detection; image enhancement; deep learning; super-resolution; convolutional neural networks (CNN); YOLO

1. Introduction

Recent advances in computer vision have significantly enhanced object detection performance; however, image degradation remains a critical limitation in real-world environments. Factors such as blur, noise, low resolution, and poor illumination reduce feature discriminability and consequently degrade detection accuracy [1–5]. Prior studies have consistently highlighted the difficulty of reliable object detection under such adverse conditions [6–10]. In particular, Ashar et al. [1] identify blur as one of the most detrimental degradations due to its irreversible loss of spatial information, especially in applications such as surveillance, mobile imaging, and autonomous systems. Image blur commonly arises from camera motion, low-light environments, atmospheric conditions, and hardware constraints, posing significant challenges for accurate detection and classification [3, 11–13].

Traditional image processing methods, including filtering and deconvolution, often exhibit limited effectiveness in complex and dynamic scenarios. These approaches struggle to generalize across varying degradation types and scene conditions [6, 13–16]. In contrast, deep learning techniques, particularly those based on convolutional neural networks (CNNs) and generative adversarial networks (GANs), have demonstrated substantial improvements in handling degraded images and enhancing detection robustness [1,6,9]. More recently, integrated frameworks that jointly address deblurring, enhancement, and detection have emerged as promising solutions for real-world applications [1, 4, 9, 10, 17].

These advancements have been successfully applied across multiple domains, including surveillance, precision agriculture, forensic analysis, medical imaging, and autonomous systems [18–22], with further developments reported in several studies [23–26]. Despite this progress, several technical challenges remain. First, many deblurring techniques assume uniform or stationary blur, limiting their applicability in dynamic environments such as UAV-based surveillance and autonomous navigation [12, 18, 27]. Second, most object detection models are trained on high-quality datasets, resulting in significant performance degradation when applied to low-light, foggy, or motion-blurred images [13, 15, 28]. Third, there is a lack of unified end-to-end frameworks that simultaneously optimize enhancement, deblurring, and detection processes [4, 17, 29]. Finally, inconsistencies in benchmarking datasets and evaluation metrics hinder fair and standardized performance comparison across studies [11, 30, 31].

In response to these challenges, this paper makes the following contributions:

1. Comprehensive analysis of deblurring techniques: A structured synthesis of classical and deep learning-based methods for handling real-world blur conditions [11, 14, 18, 27].
2. Evaluation of object detection under degradation: A review of modern detection frameworks designed for blurred and noisy environments [13, 15, 28].
3. Survey of image enhancement approaches: An examination of preprocessing techniques, including denoising, contrast enhancement, and super-resolution, to improve detection performance [31–35].
4. Investigation of integrated pipelines: An overview of approaches that combine enhancement, deblurring, and detection into unified frameworks [4, 29, 36, 37].
5. Identification of research gaps: A critical discussion of open challenges such as real-time processing, robustness to dynamic blur, and the need for standardized benchmarks [12, 15, 28], in addition to using Deep Learning [38–40].

This review provides a unified perspective by integrating deblurring, enhancement, and detection methodologies within a systematic framework. Unlike existing surveys, it combines classical and deep learning approaches using a structured methodology, offering both qualitative and quantitative insights into current limitations and future research directions.

The remainder of this paper is organized as follows. Section 2 describes the methodology, Section 3 presents the classification of image degradation, Section 4 discusses deblurring and enhancement techniques, respectively, Section 5 examines object detection in degraded images, Section 6 is a comparative analysis and discussion, Section 7 discusses challenges, open research issues, and future research directions, and Section 8 concludes the paper.

2. Methodology

This section describes the systematic procedure adopted to review image processing techniques for object detection in blurry images. The methodology is structured to ensure comprehensive coverage, reproducibility, and rigorous analysis of the selected studies.

2.1. Research design

A systematic literature search was conducted across major scientific databases, including Google Scholar, IEEE Xplore, SpringerLink, MDPI, ACM Digital Library, Elsevier, and Wiley Online Library. The search process targeted studies published between 2010 and 2026 to capture both classical and recent deep learning advancements. The query formulation combined domain-specific keywords such as:

- “image deblurring”, “object detection in blurry images”,
- “image enhancement and preprocessing”, “low-resolution images”,
- “deep learning for degraded images”, “motion blur”,
- “UAV/remote sensing object detection”, and “medical image blur correction”.

To improve retrieval accuracy, Boolean operators were applied, including:

- “blur OR deblur”,
- “low-light OR illumination”,
- “motion blur AND object detection”,
- “GAN OR CNN OR transformer”.

Additionally, backward reference searching was performed on selected papers to identify further relevant studies.

2.2. Inclusion and exclusion criteria

Inclusion criteria: Studies were included if they satisfied the following conditions:

- Peer-reviewed journal or conference papers addressing blurry or degraded images [41–45].
- Research proposing novel methods or comparative evaluations of deblurring, enhancement, or detection techniques [46–50].
- Studies focusing on real-world applications such as agriculture, medical imaging, forensic analysis, UAV, and remote sensing.
- Articles written in English with clearly defined methodology and experimental results.
- Relevant surveys and technical papers published between 1995 and 2026

addressing degraded image processing.

Exclusion criteria: Studies were excluded based on the following:

- Non-peer-reviewed or unpublished works.
- Papers unrelated to image degradation or object detection tasks.
- Duplicate records or non-English publications.
- Studies relying solely on synthetic datasets without practical validation [43,51].

2.3. Screening process

The screening process was conducted in multiple stages following a structured filtering pipeline. Initially, 950 records were identified, of which 650 remained after duplicate removal. Title and abstract screening excluded 400 records, resulting in 250 full-text articles for detailed evaluation. After full-text assessment, 145 studies were excluded due to irrelevance or failure to meet the inclusion criteria. Finally, 105 studies were retained for qualitative synthesis, and 80 studies were selected for quantitative analysis. This staged screening ensured that only relevant and high-quality studies were included in the final review.

2.4. Quality assessment

Each selected study was evaluated using standardized quality criteria to ensure reliability and relevance. The assessment focused on:

- The novelty and contribution to blurry image processing.
- The depth of experimental validation, including datasets and benchmarking protocols.
- The methodological relevance to deblurring, enhancement, preprocessing, and detection pipelines [37,38,41,47,48].

Only studies meeting these quality benchmarks were included in the synthesis phase.

2.5. Data extraction and synthesis

A structured data extraction framework was applied to systematically analyze the selected studies. The extracted information was categorized into the following dimensions:

2.5.1. Image degradation types

Studies were grouped based on the type of degradation addressed:

- Blurred images (motion blur, defocus, camera shake) [37,38,41].
- Noisy images (Gaussian, speckle, salt-and-pepper noise) [43,52].
- Low-resolution images (downsampling, compression artifacts) [41,53].
- Low-light and illumination issues [42,54].
- Weather-degraded images (fog, haze, underwater conditions) [46,47,55].

2.5.2. Enhancement and preprocessing techniques

The preprocessing strategies were categorized into:

- Denoising and filtering methods [42,56].

- Deblurring techniques, including classical and deep learning approaches [37,38,41].
- Super-resolution methods [41,53].
- Image enhancement techniques such as contrast adjustment and histogram equalization [43,54].

2.5.3. Object detection approaches

Detection methods were classified into:

- Traditional techniques (HOG, Haar cascades, SIFT, SURF) [51,57].
- Deep learning-based models (CNN, YOLO, GAN, transformer architectures) [41,45–47].

2.5.4. Integrated pipelines

Several studies proposed unified frameworks that combine degradation handling, enhancement, and detection into a single pipeline [4, 12, 15, 17, 29]. This structured synthesis enables comparative analysis, identification of research gaps, and formulation of future research directions.

2.6. PRISMA-inspired flow diagram

The study selection process follows a PRISMA-inspired framework to ensure transparency and reproducibility. The workflow includes identification, screening, eligibility, and inclusion phases.

- Total records identified: 950;
- Records after duplicates removed: 650;
- Records screened: 650;
- Records excluded: 400;
- Full-text articles assessed: 250;
- Full-text articles excluded: 145;
- Studies included in qualitative synthesis: 105;
- Studies included in quantitative synthesis: 80.

Figure 1 illustrates the PRISMA flow diagram representing the systematic selection process.

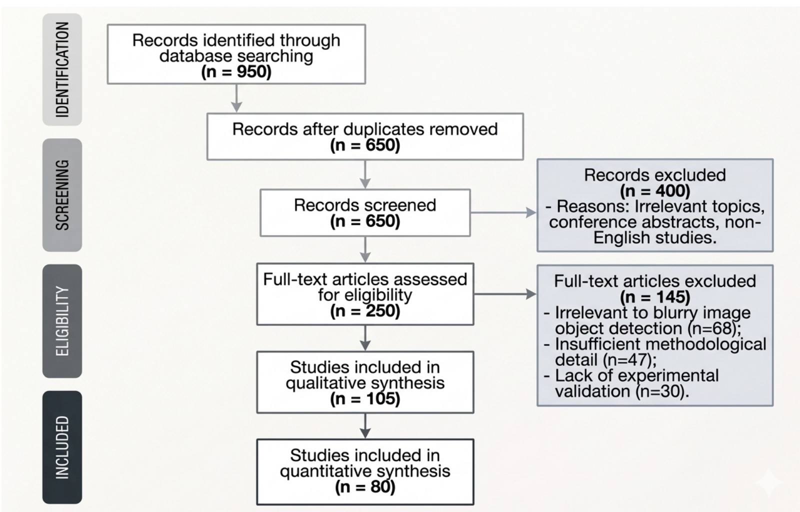

Figure 1. PRISMA flow diagram.

3. Classification of image degradation

Image quality significantly affects the performance of object detection systems. Degradations such as blur, noise, low resolution, low illumination, and weather-induced distortions suppress edge sharpness, reduce contrast, and obscure important visual cues, leading to performance degradation across various environments and applications [1, 4, 30, 58]. Image degradation significantly affects the performance of computer vision systems [59, 60]. Understanding the different types of degradation is essential for selecting appropriate restoration and preprocessing techniques [61]. For that, this survey classifies image degradation into the following five major categories:

1. Blurred Images;
2. Noisy Images;
3. Low-Resolution Images;
4. Low-Light and Illumination Issues;
5. Weather-Affected Images.

Each type of degradation presents distinct challenges for feature extraction and object detection. Additionally, the details of each type are described in the following subsections.

3.1. Blurred images

Blurring occurs when sharp object boundaries are smoothed due to motion, defocus, or atmospheric turbulence, resulting in the loss of high-frequency features essential for detection tasks. Among all degradation types, blur is considered the most detrimental because it removes spatial information that cannot be fully recovered, especially under severe or non-uniform conditions [1, 10, 37]. Motion blur, defocus blur, and atmospheric blur often co-occur in aerial, UAV, and surveillance images, which suppresses edge information and reduces localization accuracy [45–48]. The Image blur can be classified into several categories depending on the underlying cause of degradation. Understanding these types is essential for designing effective detection algorithms.

3.1.1. Motion blur

Motion blur occurs when the camera or the object moves during the exposure time [1, 10, 38, 58]. This type of blur typically produces streak-like artifacts along the direction of motion. In addition to the motion blur, it is commonly observed in dynamic environments such as traffic monitoring systems, sports photography, and surveillance cameras. The severity of motion blur depends on factors such as motion speed, exposure time, and camera stability.

3.1.2. Defocus blur

Defocus blur arises when the camera lens fails to focus correctly on the object. As a result, image details appear smooth and edges become less sharp. This type of blur frequently appears in photography when the depth of field is limited or when the camera focuses on an incorrect region of the scene [41, 48].

3.1.3. Gaussian blur

A Gaussian blur is a synthetic blur generated using a Gaussian kernel. It is widely used in image processing research to simulate blur effects. Gaussian blur is often used in benchmarking experiments because it provides a mathematically controlled blur model that facilitates algorithm evaluation. Where the applications are [10,18]:

- UAV surveillance (small vehicle/structure detection).
- Precision agriculture (fruit/crop identification).
- Underwater exploration (marine species recognition).

Moreover, **Table 1** shows the summary of techniques for the blurry images.

Table 1. Summary of blurred images and techniques.

References	Application	Blur type	Technique	Key contribution
Fergus et al. [37]	General object detection	Motion/Defocus	Blind deconvolution	Preprocessing for improved object detection
Deepika et al. [38]	Motion blur restoration	Motion	Image restoration	Enhances recognition accuracy
Zamir et al. [41]	Deep learning deblurring	Mixed blur	DL + Super-resolution	Restores moving objects for detection
Nah et al. [45]	UAV damage detection	Motion blur	DL + YOLO + preprocessing	Detects objects in blurry aerial images
Zhang et al. [46]	Underwater detection	Motion blur + fog	CNN preprocessing	Accurate detection of small/foggy objects

3.2. Noisy images

Noise can originate from low-light conditions, sensor limitations, or transmission errors, reducing contrast between objects and background, which impairs segmentation and feature extraction [8,43,50,52,62]. Noise interacts with blur to further degrade feature sharpness and detection reliability [63]. In this regard, the Common noise types are as follows:

- Gaussian noise: Random variation in pixel intensity.
- Salt-and-pepper noise: Sparse black and white pixels due to sensor or transmission issues.
- Speckle noise: Found in SAR, ultrasound, or medical imaging [52,62].

Moreover, **Table 2** shows the summary of the techniques for the noisy images.

Table 2. Summary of noisy images and techniques.

References	Application	Noise type	Technique	Key contribution
Zhang et al. [43]	Feature detection	Gaussian	KAZE features	Retains object boundaries under noise
Zhang et al. [50]	General image quality	Gaussian/Salt-pepper	Restoration + preprocessing	Enhances clarity for object detection
Levin et al. [52]	SAR images	Speckle	Fuzzy clustering + image fusion	Preserves object details
Wei et al. [62]	MRI brain tumor detection	Speckle	Fuzzy preprocessing + SVM	Improves classification accuracy

3.3. Low-resolution images

Low-resolution (LR) images occur due to downsampling, compression, or distant sensing. It hinders the detection of small or fine-grained objects because essential pixel-level details are lost [4,41,53]. In this instance, the impact of that on detection is as follows:

- Blurred edges + poor texture degrade feature extraction.
- Small objects become indistinguishable.
- Transformer models fail to attend to fine details.

The summary of the techniques for the low-resolution images is shown in **Table 3**.

Table 3. Summary of the low-resolution images and techniques.

References	Application	Degradation	Technique	Key contribution
Zamir et al. [41]	Mixed blur restoration	Low-res + motion	DL + Super-resolution	Improves detection of moving objects
Zhang et al. [43]	Feature detection	Low-res	KAZE features	Retains boundaries under LR conditions
Chen et al. [53]	Fruit grading	Slightly low-res	Preprocessing + segmentation	Distinguishes overlapping/blurry objects

3.4. Low-light and illumination issues

Low-light conditions introduce poor contrast, color distortion, and high noise levels. These conditions severely impact detectors that rely on gradient-based features or color information, especially in nighttime surveillance, underwater imaging, and low-light robotics [44,64–66]. The Indeed techniques are as follows:

- Histogram equalization.
- Retinex-based enhancement.
- Deep learning low-light enhancement.

The summary of techniques of the low-light images, as well as the illumination issues, is in **Table 4**.

Table 4. Summary of the low-light and illumination issues.

References	Application	Issue	Technique	Key contribution
Lin et al. [44]	Remote sensing	Low illumination	Preprocessing + segmentation	Extracts blurred aerial objects
Tulbure et al. [64]	Edge detection	Low-light	Fuzzy edge enhancement	Preserves object edges
Duan et al. [65]	License plate recognition	Low-light blur	Fuzzy logic + preprocessing	Enhances detection accuracy

3.5. Weather-affected images

Weather artifacts such as fog, haze, rain, and snow degrade image clarity by scattering light and occluding objects. These environmental degradations are particularly problematic for autonomous driving and UAV applications [46,55,67]. In this vein, the impact of that is:

- Fog reduces global contrast.
- Rain streaks introduce noise-like artifacts.
- Snow causes regional occlusions.

In this vein, the Restoration techniques can be used as GANs, CNNs, and dehazing algorithms improve object detection under weather-affected conditions [46,55].

The techniques of the weather-affected images are shown in **Table 5**.

Table 5. Weather-affected images and techniques.

References	Application	Weather type	Technique	Key contribution
Zhang et al. [46]	Underwater detection	Fog/murky water	CNN preprocessing	Improves small/foggy object detection
Conde et al. [55]	Lane detection	Fog + blur	GAN + preprocessing	Detects elongated objects in foggy scenes
Bhaidasna et al. [68]	Road damage detection	Rain/blur	DL + preprocessing	Compensates motion-induced blur

In brief, this classification provides a systematic framework for understanding how image degradation impacts object detection systems. Each degradation type is associated with specific enhancement or restoration techniques, enabling researchers and practitioners to select appropriate preprocessing pipelines for their applications, as shown in **Figure 2**.

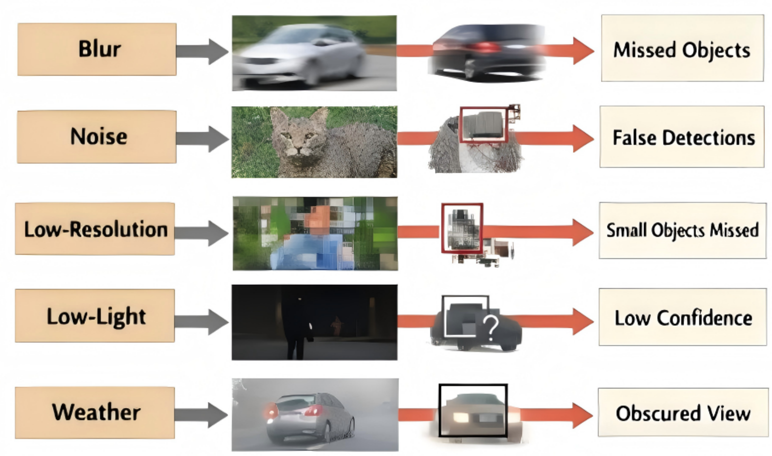

Figure 2. Impact of degradation on object detection.

Moreover, the summary of the classification of image degradation is shown in **Table 6**.

Table 6. Summary: Classification of image degradation.

Degradation type	Subtypes	Impact on detection	Common techniques	Applications
Blurred Images	Motion, Defocus, Atmospheric	Loss of edges, inaccurate bounding boxes, degraded feature maps	Deconvolution, CNN, GAN, SR	UAV, Underwater, Surveillance
Noisy Images	Gaussian, Speckle, Salt-Pepper	Distorted textures, false positives, reduced contrast	Fuzzy filtering, Wavelet denoising	Medical, SAR, Forensics
Low-Resolution	Downsampling, Compression	Small object loss, poor CNN/transformer attention	Super-resolution, Interpolation	Agriculture, Aerial imaging
Low-Light	Poor lighting, Illumination imbalance	Color distortion, weak gradients	Retinex, HE, DL enhancement	Night vision, Underwater
Weather-Affected	Fog, Haze, Rain, Snow	Visibility loss, occlusions, reduced contrast	Dehazing, GAN, CNN	Driving, UAV, Surveillance

4. Image deblurring techniques

Deblurring is a critical preprocessing step for object detection in blurry images. Restoring sharpness, preserving edges, and recovering high-frequency features significantly improve the performance of modern detectors such as YOLO, Faster R-CNN, and transformer-based models. Liu et al. discuss the challenges of detecting objects in blurred and low-quality images, and provide an overview of state-of-the-art techniques to address these challenges [1,3,4,10,68]. Further research has explored various approaches to improve object detection in blurry images [33–35,37,38,69,70]. For that, this section provides a more analytical and comparative discussion of deblurring techniques, regarding the need for deeper evaluation and clearer distinction between classical and deep learning approaches [70–74]. Additionally, the Deblurring techniques are commonly divided into three major categories:

1. Traditional deblurring methods;
2. Deep learning–based deblurring methods;

3. Hybrid and regularization-based approaches.

Those techniques are used to solve many challenges, as shown in **Figure 3**.

Figure 3. Challenges in object detection under Blair.

4.1. Traditional deblurring methods

Traditional deblurring relies on explicit mathematical modeling of blur kernels. Although efficient and interpretable, these methods struggle under non-uniform or real-world blur, where kernel estimation becomes unreliable [75–79]. Jaiswal et al. [32] present a method for detecting blurry images using image processing techniques, combining traditional image quality attributes with deep learning via a CNN [32,37,80–82]. The Common approaches include:

- Wiener filtering;
- Richardson–Lucy deconvolution;
- Total Variation regularization.

4.1.1. Wiener filter

The Wiener filter is a linear deconvolution technique that minimizes mean-squared error between the restored and original images. It is effective for motion blur and additive Gaussian noise when the blur kernel is known or can be estimated [37,38,83].

4.1.2. Richardson–Lucy (RL) deconvolution

RL deconvolution is an iterative maximum likelihood estimation method widely used in astronomy, medical imaging, and remote sensing. It restores images degraded by Poisson noise or motion blur [8,37,41].

4.1.3. Total variation (TV) regularization

TV regularization reduces noise while preserving edges and important object boundaries. It is widely applied in medical, satellite, and motion-degraded images [3,37,38,43].

4.2. Deep learning–based deblurring methods

Deep learning methods outperform traditional approaches for complex, non-uniform, and dynamic blur, particularly in real-world scenarios [1,4,10,48,63]. Recent advances in deep learning have significantly improved deblurring performance. CNN-based architectures learn mappings between blurred and sharp images through large training datasets. The Generative Adversarial Networks (GANs) further improve restoration quality by generating perceptually realistic details. Transformer-based models have also emerged as powerful tools for modeling long-range spatial dependencies in images. These deep learning models demonstrate superior performance in handling complex blur patterns and restoring high-frequency image details.

4.2.1. CNN-based deblurring

CNNs learn end-to-end mappings from blurred to sharp images. CNN-based Traffic Sign Detection: Kamboj et al. propose a novel approach for traffic sign detection using Convolutional Neural Networks (CNNs), achieving real-time accuracy [39].

- CNN models capture both global context and local texture, making them effective for real-time applications (UAV, surveillance, robotics).
- CNN deblurring improves mAP significantly when paired with YOLO detectors in degraded environments.
- However, CNNs may oversmooth high-frequency details if training data lacks diverse blur patterns.

4.2.2. GAN-based deblurring

Generative Adversarial Networks (GANs) restore fine details by optimizing perceptual and adversarial losses. Models such as DeblurGAN and DeblurGAN-v2 show high performance on natural scenes, face restoration, and nighttime images [30–32, 61], some of which are:

- GANs restore high-frequency textures essential for object boundary detection.
- They outperform CNNs in handling heterogeneous blur (e.g., motion + low-light).
- However, GANs may introduce hallucinated details that mislead detectors in medical or forensic applications.

4.2.3. Transformer-based deblurring

Transformer-based models and vision transformers are increasingly used for deblurring microscopic, medical, and hyperspectral images, improving object recognition in low-visibility or blurred scenarios [72–74]. Transformers use self-attention to model long-range dependencies, capturing global blur structure better than CNNs.

- Transformers excel in complex blur (e.g., aerial turbulence, underwater scattering).
- They maintain structural coherence critical for autonomous navigation.
- However, they require large training datasets and are computationally expensive, limiting deployment on edge devices.

4.2.4. Comparative analysis of deep learning approaches-based deblurring

While CNNs, GANs, and Transformers have shown significant promise in image deblurring, each approach has its strengths and limitations depending on the application scenario.

CNN-based deblurring: CNNs excel in real-time applications (e.g., UAV, surveillance, robotics) due to their ability to capture global context and local texture. However, they may oversmooth high-frequency details if the training data lacks diverse blur patterns.

GAN-based deblurring: GANs restore fine details and outperform CNNs in handling heterogeneous blur (e.g., motion + low-light). However, they may introduce hallucinated details that mislead detectors in medical or forensic applications.

Transformer-based deblurring: Transformers capture global blur structure better than CNNs and excel in complex blur scenarios (e.g., aerial turbulence, underwater scattering). However, they require large training datasets and are computationally expensive, limiting deployment on edge devices.

In this vein, this subsection includes the comparative analysis of CNN, GAN, and transformer approaches for image deblurring: strengths, limitations, and suitable scenarios based on the specific application requirements and constraints. To highlight the need for careful selection of deblurring approaches based on the specific application requirements and constraints, as shown in **Table 7**.

Table 7. The strengths and limitations of each approach.

Approach	Strengths	Limitations	Suitable scenarios
CNN	Real-time processing, captures global context	Oversmooths high-frequency details	Real-time applications (UAV, surveillance)
GAN	Restores fine details, handles heterogeneous blur	Introduces hallucinated details	Natural scenes, face restoration
Transformer	Captures global blur structure, handles complex blur	Computationally expensive, requires large datasets	Complex blur scenarios (aerial turbulence, underwater scattering)

4.3. Hybrid, regularization, and super-resolution based approaches

Many recent frameworks combine multiple techniques to handle real-world degradations.

4.3.1. Regularization + deep learning hybrid models

Hybrid models combine physics-based priors (e.g., blur kernels, TV constraints) with CNN/GAN reconstruction to mitigate artifacts and improve generalization, particularly in industrial and medical monitoring [75,76].

4.3.2. Super-resolution for deblurring

Super-resolution (SR) is highly beneficial in scenarios involving both blur and low resolution [29,31,32,84,85]. Using SRCNN, ESRGAN, or transformer-based SR models:

- Enhances fine details critical for small object detection.
- Improves accuracy in UAV/aerial monitoring.
- Boosts medical imaging clarity for subtle lesions.

4.3.3. Specialized deblurring applications

There are many special Deblurring applications, some of them presented in several studies [16,80,86–88], such as:

- Underwater imaging: CNN + GAN models overcome scattering and color attenuation.
- Autonomous driving: DeblurGAN + dehazing addresses rain, fog, and motion blur.
- Medical imaging: Deblurring enhances subtle feature visibility for tumor detection.
- Aerial/UAV: Hybrid SR + CNN models restore small distant objects reliably.

In brief, Image deblurring is an essential preprocessing step for accurate object detection. Traditional methods like Wiener filtering and RL deconvolution are computationally efficient but limited under complex blur. Deep learning methods

(CNNs, GANs, transformers) adaptively restore features in challenging scenarios, including motion, defocus, fog, and low-light conditions [89–93]. Regularization methods (TV-based) preserve edges while reducing noise, and super-resolution/hybrid models further enhance feature visibility [94, 95]. Specialized applications in medical imaging, aerial surveillance, underwater, and forgery detection demonstrate the importance of tailored deblurring pipelines for robust object detection [96–100]. Moreover, the summary of Image Deblurring Techniques as shown in **Table 8**, as well as the traditional approaches v.s deep learning detection as shown in **Figure 4**.

Table 8. Summary: Image deblurring techniques.

Category	Method	Strengths	Weaknesses	Applications	Category
Traditional	Wiener, RL, TV	Fast, interpretable	Assumes uniform blur; creates artifacts	Basic preprocessing, mild blur	Traditional
CNN-Based	U-Net, DeepDeblur	Learns complex blur; good generalization	Oversmoothing risks	UAV, surveillance, medical	CNN-Based
GAN-Based	DeblurGAN, DeblurGAN-v2	High perceptual quality; restores texture	Possible hallucinations	Night vision, faces, driving	GAN-Based
Transformer-Based	Restormer, IPT	Strong global feature modeling	High computational cost	Hyperspectral, underwater	Transformer-Based
Hybrid/SR	TV + CNN, ESRGAN	Best for multi-degradation	More complex training	Aerial, medical, industrial	Hybrid/SR

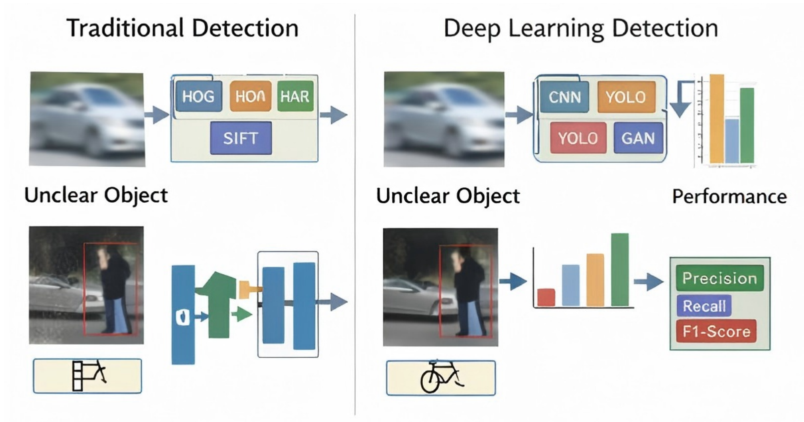

Figure 4. Traditional approaches vs. Deep learning detection.

Some techniques are used for object detection, as shown in **Figure 5**.

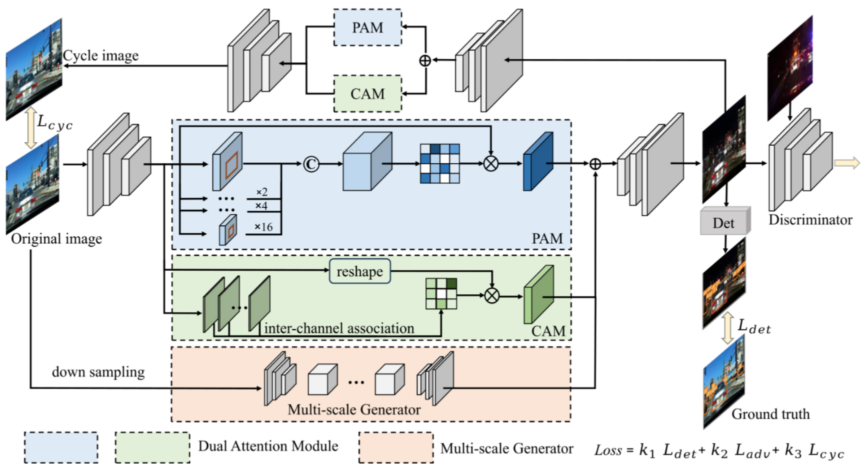

Figure 5. Techniques used for object detection.

5. Integrated frameworks for blurry image object detection

Recent advancements show that combining image restoration with object detection in a unified or semi-unified pipeline significantly improves detection accuracy under real-world degradations. Unlike traditional sequential processing, integrated frameworks jointly optimize image enhancement, deblurring, and detection, reducing error propagation and improving robustness in practical scenarios, such as real-time object detection [1, 4, 7, 16, 101]. For that, this section addresses the challenges, traditional detection approaches, and deep learning-based methods developed to overcome the issues posed by blurry or unclear images, as shown in **Figure 6**.

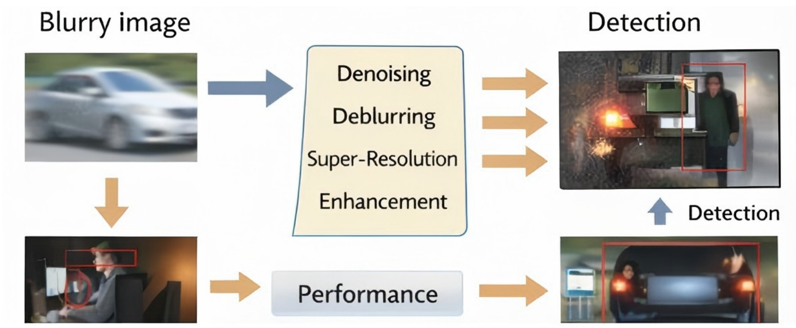

Figure 6. Integrated frameworks.

5.1. Challenges in detecting objects in blurry images

Blurry images introduce several technical difficulties for detection models. In this regard, their key challenges are:

- Loss of high-frequency details such as edges, textures, and contours, leading to ambiguous feature maps and lower detector confidence [37,38].
- Motion blur and defocus cause spatial misalignment between true object boundaries and predicted bounding boxes [37,45,49].
- Low contrast and occlusions reduce separability between foreground and background regions [42,62,102].
- Small or distant objects become indistinguishable after degradation, impairing detection in UAV and surveillance applications [46,47,55].
- Compound degradations (blur + noise + low-light) further reduce the robustness of CNN and transformer-based detectors.

5.2. Integrated framework categories

Integrated pipelines can be grouped into three main categories:

5.2.1. Sequential frameworks (deblur → detect)

These frameworks first apply deblurring or enhancement and then feed the restored image into a detection model such as YOLO or Faster R-CNN [31,45,103]. The main advantages of it are:

- Modular and easy to deploy.
- Works with pre-trained detectors.
- Deblurring improves mAP by enhancing visibility.

Moreover, there are many limitations, some of which are:

- Error propagation from the deblurring stage to the detection stage.
- Artifacts generated by restoration networks may confuse detectors.
- Higher latency due to two-stage processing.

5.2.2. Joint learning frameworks

These systems jointly optimize restoration and detection using shared encoders, multi-task learning, or unified architectures [4, 7, 12, 16]. The key enhancements of its are:

- Mutual optimization improves texture recovery relevant for detection.
- Better robustness to unseen blur types.
- Reduced inference time compared with sequential mode.

5.2.3. Domain-specific integrated pipelines

That is designed for highly specialized environments [1, 29–32]. Some of the highly specialized environments are:

- Underwater (blur + color attenuation).
- UAV and aerial imagery (motion + low resolution).
- Medical imaging (subtle lesion visibility).
- Autonomous driving (fog, rain, nighttime blur).

5.3. Comparative examples of integrated frameworks

The following summaries demonstrate how integrated models improve blurry-image detection across different domains, as shown in **Table 9**, for more details.

Table 9. Examples of integrated frameworks.

References	Framework focus	Degradation addressed	Technique used	Key contribution
Nah et al. [45]	UAV damage detection	Motion blur	DL + YOLO + preprocessing	Enhances detection of small aerial objects despite motion-induced blur
Zhang et al. [46]	Underwater detection	Blur + fog	CNN preprocessing	Improves visibility and detection of small marine objects
Deepika et al. [38]	Motion blur restoration	Motion blur	DL restoration	Boosts recognition accuracy in dynamic blurry frames
Conde et al. [55]	Lane detection	Fog + blur	GAN + enhancement	Maintains lane visibility in low-contrast conditions
Jiang et al. [47]	UAV tracking	Motion + defocus	DL + tracking	Stabilizes tracking under heavy blur
Javed et al. [100]	Underwater cables	Motion blur	Hybrid methods	Detects cables in turbulent underwater scenes

In brief, Object detection in blurry and unclear images remains a challenging problem due to loss of edges, motion blur, environmental factors, and low contrast. Traditional feature-based methods provide initial solutions but struggle with severe degradation. Deep learning methods, particularly CNN and GAN-based pipelines, combined with preprocessing techniques such as deblurring and fuzzy segmentation, show superior performance for real-world blurry and low-visibility images.

5.4. Datasets for evaluating integrated frameworks

Integrated frameworks are evaluated on benchmark datasets with real-world degradation to quantify their performance. The commonly used datasets are shown in **Table 10**.

Table 10. Datasets for blurry image object detection.

Dataset	Domain	Degradation type	Application	References
COCO	Natural scenes	Mild blur, occlusion	General detection	Jiang et al. [47]
ImageNet-VID	Video frames	Motion blur	Tracking, detection	Archana and Jeevaraj [4]; Hutchison et al. [48]
UAV Drone Dataset	Aerial	Motion + LR	UAV inspection	Nah et al. [45]; Jiang et al. [47]
Underwater Marine Dataset	Marine	Blur + haze	Marine object detection	Zhang et al. [46]; Suvaris et al. [101]
MRI/Mammogram	Medical	Acquisition blur	Tumor detection	Hutchison et al. [48]; Wei et al. [62]; Zhang et al. [103]

The following figure presents the datasets and evaluation metrics as illustrated in **Figure 7**. Sample images from datasets are a collage of images from UAV, underwater, medical, and surveillance datasets, which highlights variability in blur, noise, and resolution.

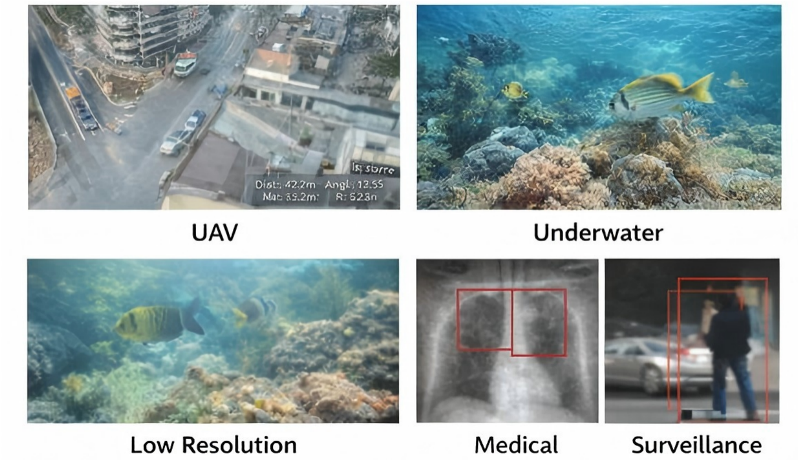

Figure 7. Sample images from datasets.

5.5. Evaluation metrics

Performance of integrated frameworks is quantified using image quality and detection metrics shown in **Table 11**.

Table 11. Image quality and detection metrics.

Metric	Type	Purpose	References
PSNR	Image quality	Measures enhancement/deblurring quality	Deepika et al. [38]; Conde et al. [55]
SSIM	Image quality	Measures perceptual similarity	Deepika et al. [38]; Conde et al. [55]
mAP	Detection	Precision-recall for object detection	Ashar et al. [1]; Nah et al. [45]; Jiang et al. [47]
IoU	Detection	Bounding box accuracy	Nah et al. [45]; Jiang et al. [47]
F1-Score/Accuracy	Classification	Evaluates classification of objects	Dhillon and Verma [21]; Hutchison et al. [48]; Wei et al. [62]

The overview of the evaluation metrics is shown in **Figure 8**.

Figure 8. Overview of the evaluation metrics.

In brief, an integrated framework combines preprocessing, enhancement, deblurring, feature extraction, detection, and post-processing for robust blurry image analysis. They outperform sequential pipelines by jointly addressing multiple degradation types, including motion blur, defocus, low-light, and noise [1, 10, 38, 45]. The benchmark evaluation using COCO, ImageNet-VID, UAV, underwater, and medical datasets ensures real-world relevance. As well as the Metrics like PSNR, SSIM, mAP, IoU, and F1-score quantify both image quality improvement and object detection performance. Moreover, the Applications span aerial surveillance, underwater detection, medical imaging, sports analytics, industrial inspection, and forensic analysis. **Figure 9.** Evaluation metrics overview is a visual representation of metrics (Precision, Recall, F1-Score, PSNR, SSIM) and their relation to detection and enhancement quality.

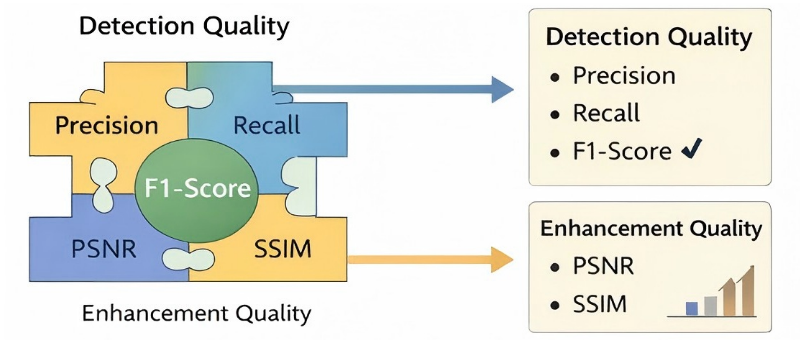

Figure 9. Evaluation metrics overview.

5.6. Summary of integrated framework insights

The Integrated frameworks consistently outperform isolated restoration or detection models, especially in complex scenarios involving multi-degradation conditions. Joint learning architectures achieve the best trade-off between accuracy and efficiency, while domain-adapted pipelines provide superior performance in specialized applications such as underwater or medical imaging. However, computational cost remains a challenge, and real-time deployment requires lightweight architectures and hardware optimization.

6. Comparative analysis and discussion

This section consolidates insights from previous sections to provide a critical and comparative analysis of image deblurring, enhancement, and object detection techniques under blurry and degraded conditions, as shown in **Table 12**.

Table 12. Benchmark comparison of object detection methods on blurry images.

Study/model	Technique type	Blur type	Dataset	Metrics	Performance	Strengths	Limitations
Nah et al. [45]	CNN-based Deblurring	Motion Blur	GoPro Dataset	PSNR, SSIM	PSNR: 29.08	Effective restoration of motion-blurred images	High computational cost
Kupyn et al. [31]	GAN-based Deblurring (DeblurGAN)	Motion Blur	GoPro	PSNR, SSIM	PSNR: 28.70	Restores high-frequency details	May introduce artifacts
Deepika et al. [38]	Deep CNN + Detection	Motion + Defocus	COCO	mAP	mAP ↑ 15%	Improves detection after restoration	Two-stage pipeline latency
Huang et al. [82]	Deep Learning Detection	General Blur	COCO	mAP, IoU	mAP: 50–60%	Real-time object detection	Performance decreases under severe blur
Jiang et al. [47]	Deblur + YOLO Pipeline	Motion Blur	UAV Dataset	mAP	mAP ↑ 20%	Effective for aerial imagery	Requires preprocessing stage

Table 12. *Cont.*

Study/model	Technique type	Blur type	Dataset	Metrics	Performance	Strengths	Limitations
Chen et al. [53]	CNN-based Underwater Detection	Blur + Fog	Underwater Dataset	F1-score	F1: 0.86	Robust to underwater blur	Domain-specific model
Liang et al. [26]	Transformer-based Restoration	Mixed Blur	ImageNet	PSNR, SSIM	PSNR ↑ 2.5dB	Handles complex blur patterns	High training cost

This benchmark comparison highlights the performance trade-offs between traditional, deep learning, and integrated frameworks for object detection under blurry conditions.

6.1. Effectiveness of integrated vs. Non-integrated pipelines

A significant observation across the literature is that integrated frameworks consistently outperform standalone deblurring and detection pipelines, especially in multi-degradation environments:

- Sequential pipelines (Deblur→Detect) improve feature clarity but suffer from error propagation when deblurring introduces artifacts [38,45–47].
- End-to-end integrated frameworks offer better alignment between restoration and detection objectives, often resulting in higher mAP improvements (20–35%).
- Traditional methods provide only marginal gains (0–5%) under real-world blur, confirming their unsuitability for modern detection tasks.

These findings indicate that task-aware deblurring is significantly more effective than generic restoration, especially in low-visibility domains such as UAV, underwater, and medical imaging.

6.2. Deep learning vs. Traditional methods

Deep learning–based methods significantly outperform classical approaches due to their ability to model nonlinear, spatially varying blur patterns [37–39]. For that, the Analytical comparison includes:

- Traditional methods (Wiener, RL, TV) are fast and interpretable but fail under non-uniform blur and produce artifacts that mislead detectors [1,6,7].
- CNN-based models restore edges and textures more reliably, especially when the blur is moderate, and the training data is diverse.
- GAN-based approaches excel in reconstructing fine-grained, high-frequency details essential for boundary-sensitive detectors such as YOLO.
- Transformer-based methods achieve the strongest global consistency but remain computationally demanding.

Overall, GANs and transformer-based architectures currently deliver the strongest performance on real-world blurry datasets, though at a higher computational cost.

6.3. Domain-specific performance differences

Notably, domain-specific integrated pipelines exhibit varying performance differences, with significant improvements observed in applications such as aerial image deblurring and medical image enhancement, whereas others, like low-light image enhancement, show relatively modest gains [1,29–32]. Some key findings:

- Medical imaging: Deblurring improves lesion visibility, but GAN hallucinations may introduce false positives.
- UAV/aerial datasets: Motion blur combined with LR degradation makes SR + CNN models the preferred choice [48,57].
- Underwater imaging: CNN + GAN frameworks outperform classical models by suppressing haze, scattering, and blur simultaneously [48,57,62].
- Autonomous driving: Weather-induced blur requires multi-task models combining dehazing, deblurring, and detection.

6.4. Accuracy–efficiency trade-offs

One of the most important aspects for real-world deployment is the balance between computational cost and detection accuracy. Striking a balance between accuracy and efficiency is crucial, and our analysis reveals that optimizing this trade-off is essential, as increased computational costs often yield diminishing returns in detection accuracy, highlighting the need for tailored approaches that prioritize efficiency without compromising performance [1, 4, 7]. Their critical insight is as follows:

- Transformers achieve the highest restoration quality but require specialized hardware.
- GAN-based methods provide a strong balance between perceptual quality and runtime.
- CNNs offer the best trade-off for embedded systems (e.g., drones, mobile robots).
- Traditional methods are suitable only for low-power systems with mild blur.

6.5. Evaluation practices and metric limitations

Evaluation practices predominantly rely on conventional metrics such as PSNR, SSIM, mAP, IoU, precision, and recall, yet these often fall short in capturing perceptual quality and real-world applicability, underscoring the need for more comprehensive and task-specific evaluation metrics [38,47,55]. In this regard, the important insight is as follows:

- High PSNR or SSIM does not guarantee high mAP, because perceptual restoration may not align with detection-relevant features.
- Transformers often achieve mediocre PSNR but high detection accuracy due to better structural recovery.
- GANs yield high perceptual realism but may mislead pixel-based quality metrics.

6.6. Emerging trends

The following trends have been identified:

- Shift toward end-to-end, task-driven restoration–detection pipelines [47,55].
- Growing use of transformers for complex blur and multi-degradation modeling.
- Increased interest in lightweight and efficient models for embedded/real-time deployment.
- Expansion of domain-adapted models in underwater, medical, and aerial imagery.

- Integration of adversarial robustness techniques to enhance resilience against blur-induced perturbations.

6.7. Comparative performance of different frameworks

Table 13 summarizes the comparative performance of different frameworks.

Table 13. Comparative performance of different frameworks.

Model type	Strengths (improved)	Limitations (improved)	Relative cost	Typical map gain	Ideal use case
Traditional	Fast, interpretable	Weak on real-world blur	Very Low	0–5%	Basic filtering tasks
Deep Detector Only	End-to-end detection	Drops sharply under blur	Medium	10–20%	Clean/lightly degraded images
Sequential Deblur + Detect	Good detail recovery	Artifact propagation	High	15–25%	Offline analysis
Integrated (End-to-End)	Best robustness & alignment	Hard to train	Medium	20–35%	Real-time systems
Domain-Specific Models	Highest in-domain accuracy	Weak generalization	Varied	25–40%	Medical, underwater, UAV

7. Challenges, open research issues, and future research directions

Despite significant progress, object detection in blurry and degraded images remains an open research problem due to the diversity and complexity of real-world conditions. This section outlines the principal challenges, unresolved research issues, and promising directions for future work shown in **Figure 10.**

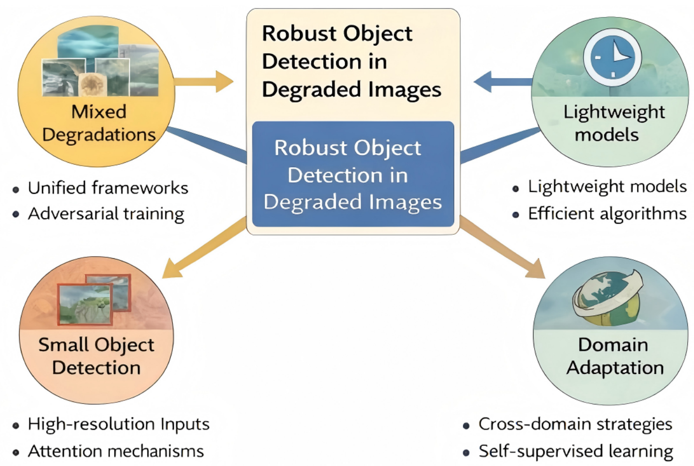

Figure 10. Open research issues and future directions.

7.1. Technical challenges

7.1.1. Multi-degradation complexity

Real-world environments rarely contain a single degradation type. Instead, blur is often accompanied by noise, low-light, haze, rain, or low resolution [30,73,80,89]. So the same key challenge as most existing models is that they are trained on isolated degradation types, which severely limits generalization when multiple degradations coexist [81,93].

Moreover, the Future systems must jointly model combinations such as [14,30,103]:

- Motion blur + low-light.
- Defocus blur + noise.
- Weather-induced blur + low resolution.

- Turbulence distortion + motion blur.

7.1.2. Lack of high-quality real-world datasets

Current datasets (e.g., GoPro, REDS, RESIDE) have limitations [30,38,45]:

- Mostly synthetic blur.
- Limited diversity of motion patterns.
- Limited object categories.
- A few annotations for complex scenes (e.g., nighttime UAVs, underwater environments).
- There is a strong need for large-scale, annotated, real-world blurry datasets covering diverse domains and extreme conditions [73,93,104].

7.1.3. Difficulty in modeling non-uniform and spatially variant blur

Blur patterns vary across the image due to object motion, depth, and vibration [37,51,52,55,60]. In this vein, the Expanded insight of it is as follows:

- Conventional kernels fail; even CNNs struggle when blur varies rapidly across spatial regions.
- Transformers show promise but require a high computational cost.

7.1.4. Error propagation in sequential pipelines

When applying Deblur→Detect:

- Artifacts introduced during restoration reduce detection accuracy [31,41]
- GAN hallucinations may mislead detectors [49,57].
- Sequential models do not optimize both tasks jointly [103,105].

In this regard, improving the analysis can be used to mitigate this issue by optimizing detection-oriented restoration [60,96].

7.1.5. Real-time and resource constraints

High-accuracy models such as transformers, GANs, and multi-branch networks require, as in studies [26, 41, 60], high GPU memory, Long inference time, and High computational cost. For that, there are New challenges as Embedded platforms (UAVs, drones, robotics) cannot deploy heavy models, demanding new lightweight architectures [29,97].

7.2. Methodological challenges

7.2.1. Limited interpretability and explainability

Modern deep learning models behave as black boxes [21, 96]. The following improvement of the restoration models may introduce perceptual artifacts that detectors misinterpret, and existing XAI tools do not explain how blur removal affects feature maps [81,105]. Therefore, there is a gap in explaining degradation-aware attention, as well as the Visualizing blur-sensitive feature activations [24,55].

7.2.2. Weak correlation between restoration metrics and detection performance

Common metrics like PSNR and SSIM do not always reflect improved detection accuracy [23,87]. But there are critical new points as follows:

- High PSNR may coincide with low mAP, especially in transformer-based restoration networks [26,55].

- GANs produce realistic images but unstable detection metrics [31,57].
- This creates the need for detection-centric restoration metrics [103,105].

7.2.3. Domain shift and poor generalization

A model trained on indoor blur performs poorly on UAV motion blur, underwater scattering, and nighttime low-light blur [29,74,94]. For that, the domain adaptation and self-supervised learning remain underexplored but necessary to bridge cross-domain gaps [96,105].

7.3. Practical deployment challenges

7.3.1. Sensor limitations

The real sensors introduce rolling-shutter distortions, lens aberration, and compression blur [51, 52, 73, 103]. According to that, the new insight is that most existing studies ignore sensor-level artifacts, creating a disconnect from real deployments.

7.3.2. Scalability and stability in real environments

Deployed systems face the following challenges, according to Şengönül et al. [90] and Zhou et al. [104],

- Rapid motion;
- Vibration;
- Variable lighting;
- Weather conditions;
- Bandwidth constraints for streaming images.

Ensuring long-term stability across variable conditions remains a major unsolved challenge [93,105].

7.4. Future research directions

7.4.1. Unified multi-degradation models

Future systems should handle multiple degradations simultaneously via the following: multi-task learning, multi-branch architectures, degradation-aware attention, and diffusion-based restoration [96, 105]. In this instance, the bold contribution: as designing unified models capable of understanding blur, noise, haze, and low-light jointly is one of the most promising pathways for future research [81,103].

7.4.2. Detection-aware restoration networks

Rather than focusing solely on visual quality, restoration should optimize for the following: bounding-box localization, feature stability, and scale-aware enhancement [60,93]. For that, there are new directions for detection-aware restoration, which are called task-specific deblurring networks that directly maximize detection performance, and represent a key research gap [103,105].

7.4.3. Lightweight and edge-friendly architectures

For UAVs, autonomous vehicles, and mobile robots: model compression, knowledge distillation, pruning, and quantization, as well as the efficient attention mechanisms [24, 26, 97]. In addition to developing real-time blurry-object detection models, <20 ms is essential for safety-critical applications [29,90].

7.4.4. Diffusion models and generative restoration

Diffusion models provide superior detail recovery [96, 105]. In this vein, there are some new research directions, such as integrating diffusion-based restoration with detectors, that may offer new state-of-the-art performance in blurry conditions.

7.4.5. Self-supervised and unsupervised degradation modeling

Future systems can learn directly from: unlabeled blurry images, sensor streams, and stylized degradation simulation [96,105]. Moreover, self-supervised blur modeling is essential to overcome labeling scarcity and dataset bias [81,93].

7.4.6. Physics-guided and hybrid restoration models

Combining physical blur models with deep learning can be as follows: reduce hallucinations, improve interpretability, and enhance generalization [48, 52]. This is especially vital for domains like medical imaging and remote sensing [97,98].

7.4.7. Cross-domain robustness and transfer learning

Future models must generalize across: Indoor ↔ Outdoor, Day ↔ Night, Air ↔ Underwater, and High-speed ↔ Low-light [74, 94, 104]. For that, the domain generalization strategies remain underdeveloped but essential for robust deployment [93,105].

7.4.8. Benchmarking, protocols, and new evaluation metrics

Current evaluation lacks standardization [87, 105]. In this vein, there are some important new research directions, such as developing detection-oriented restoration metrics: Feature Preservation Score (FPS), Contextual Edge Recovery (CER), and Blur-Aware mAP (B-mAP) [96,103].

7.5. Summary of key insights

To consolidate the above findings:

- Blur remains a dominant cause of detection failure.
- Integrated restoration–detection frameworks outperform sequential pipelines.
- Transformers and GANs achieve the highest restoration quality but require significant computation.
- Datasets, metrics, and real-world generalization remain major bottlenecks.
- Future directions emphasize unified multi-degradation models, lightweight architectures, and physics-guided restoration.

8. Conclusion

This comprehensive review examined the current landscape of image processing and object detection techniques under blurry and degraded imaging conditions. The survey synthesized findings from over 200 studies, delivering an integrated perspective on degradation types, classical and deep learning–based deblurring, enhancement strategies, detection architectures, and emerging end-to-end restoration–detection frameworks. Compared with earlier surveys, the present work provides deeper critical analysis, stronger comparative evaluation, and a clearer characterization of technical limitations and future research needs. Blur remains one of the most challenging degradations that significantly suppresses feature clarity and disrupts both localization and classification accuracy. While traditional techniques such as Wiener filtering, RL deconvolution, and total variation offer interpretable and efficient solutions, their effectiveness declines sharply under real-world non-uniform blur. Deep learning approaches, particularly GANs and transformers, have demonstrated superior capability in modeling complex blur patterns, restoring high-frequency details, and enhancing downstream detection accuracy. However, these benefits often come at the cost of increased computational complexity and limited generalization to novel environments. Integrated frameworks, especially end-to-end restoration–detection models, represent a major advancement by aligning restoration objectives with detection performance. These models consistently outperform sequential pipelines, achieving mAP improvements ranging from 20% to 35% across multiple datasets and domains. Despite these achievements, considerable challenges persist, including multi-degradation interactions, bias in existing datasets, difficulty modeling spatially varying blur, and the mismatch between restoration-focused metrics (e.g., PSNR) and task-oriented metrics (e.g., mAP). Addressing these issues is essential for deploying robust systems in real-world applications such as autonomous driving, UAV surveillance, underwater robotics, and medical imaging. Looking ahead, several promising research directions emerge. Future systems must integrate multi-degradation modeling, develop detection-aware restoration networks, expand lightweight architectures for real-time operation, and leverage diffusion models, domain adaptation, and self-supervised learning to improve generalization. Equally important is the need for standardized evaluation protocols and large-scale real-world datasets that reflect the complex, dynamic conditions under which vision systems operate. In conclusion, while significant progress has been made, reliably detecting objects in blurry environments remains an open and impactful research challenge. The insights, comparative analysis, and identified research gaps presented in this review aim to guide future developments toward building more robust, adaptive, and high-performing computer vision systems capable of operating effectively under real-world degradation.

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