

Data Quality Analysis Framework for Defense Objective Detection Systems

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Abstract—Modern defense systems have increasingly adopted object detection technologies to enhance operational capabilities across surveillance, threat assessment, and tactical intelligence applications. However, existing image quality evaluation methods rely heavily on global metrics, which fail to capture the object-specific quality characteristics that critically influence detection performance in defense scenarios where environmental conditions and operational constraints create unique challenges. To address these fundamental limitations, we present a comprehensive data quality inspection framework that systematically employs 302 quality metrics organized across 14 specialized categories, enabling quantitative assessment of image datasets without requiring expensive computational infrastructure. Throughout extensive evaluation using the PASCAL VOC dataset, our GPGPU-based parallel processing system achieves over 100 images/sec throughput while generating comprehensive quality analysis, demonstrating both technical feasibility and cost-effectiveness for defense organizations with varying computational resources.

Index Terms—Data Quality, Object Detection, Defense AI

I. INTRODUCTION

Computer vision technologies have attracted significant attention across various industries, with automated object detection systems demonstrating remarkable capabilities in surveillance and threat assessment applications. Defense organizations have increasingly adopted these advances in civilian computer vision, fundamentally transforming military operational landscapes through sophisticated automated detection capabilities that support critical missions such as surveillance, threat identification, equipment monitoring, and tactical intelligence collection, while reducing personnel exposure in hostile environments [1]. As object detection systems are used for various missions that span multiple operational domains, the need for systematic data quality assessment has become critical to ensure consistent performance.

However, this advancement results in complex challenges for maintaining reliable detection performance across diverse environmental conditions characteristic of defense operations. Unfortunately, unique constraints in defense environments make reliable performance evaluation difficult due to security classifications that limit the availability of the data set, operational restrictions that restrict the comprehensive collection of data, and environmental factors such as camouflage technologies, adverse weather conditions and equipment limitations that substantially affect image quality and subsequent detection

accuracy [2]. Despite these validation challenges, our approach leverages publicly available datasets, specifically PASCAL VOC [10], which contain complexities such as object occlusion by terrain, diverse object sizes, and varying illumination that are applicable to defense scenarios where secure access to classified imagery is restricted.

These challenges arise because conventional image quality assessment approaches do not meet the specialized requirements of defense applications, where detection performance must be maintained across diverse operational environments while consistently achieving optimal detection accuracy [3]. Existing image quality evaluation methods that are highly based on global metrics suffer from fundamental limitations in addressing the dual requirements of maintaining high detection accuracy under the security and operational constraints typical of defense environments [4]. Despite their importance, there are few studies on comprehensive data quality assessment frameworks specifically designed for defense object detection applications that can operate effectively with limited computational resources.

In this paper, we introduce a comprehensive data quality analysis framework designed specifically for object detection applications in defense environments that enables cost-effective quality assessment without requiring expensive server infrastructure. Our main idea is to systematically organize 302 established quality metrics across 14 specialized categories to overcome existing evaluation limitations. This enables quantitative analysis of image characteristics that directly influence detection performance in military contexts. Our novel approach employs GPGPU-based parallel processing that achieves 101.76 images/sec throughput while maintaining comprehensive assessment capabilities.

Our contributions are outlined as follows:

- We develop a systematic data quality inspection framework that employs 302 comprehensive metrics across 14 categories, specifically designed for cost-effective quality assessment in defense object detection applications.
- We implement a GPGPU-based parallel processing system by minimizing CPU-GPU data transfer overhead, enabling comprehensive analysis without expensive computational infrastructure.

- We propose a framework to quantitatively analyze defense data and demonstrate its capability to diagnose data quality issues using a general-purpose dataset.

Outline. The remainder of this article is organized as follows. Section II presents the background in image data quality assessment for defense applications. Section III describes our comprehensive methodology, including the 302 metric framework and GPGPU-based processing architecture. Section IV presents experimental results and analysis demonstrating the framework's effectiveness. Section V discusses related work in quality assessment frameworks and defense-specific computer vision systems. Finally, Section VI concludes the paper and discusses integration opportunities with defense technologies.

II. BACKGROUND

A. Image Quality Assessment(IQA)

Image quality assessment refers to computational techniques designed to quantitatively evaluate image characteristics directly influencing detection model performance and operational effectiveness. Image quality assessment aims to provide objective measures that correlate with human visual perception and automated detection system requirements, allowing systematic evaluation of image suitability for computer vision applications [5].

Modern quality assessment approaches can be categorized into three primary methodologies based on their reference requirements. Full-reference methods compare processed images against perfect reference versions using pixel-wise similarity measures, while reduced-reference methods utilize partial reference information to evaluate specific quality aspects. No-reference methods assess quality without requiring reference images, employing statistical models trained on perceptual quality databases to predict image characteristics [6].

Owing to the strong correlation between image quality characteristics and detection model performance, systematic quality assessment has become essential for maintaining consistent detection accuracy across diverse operational conditions [7]. The main advantage of systematic quality assessment lies in its ability to predict detection model performance based on quantifiable image characteristics, enabling proactive quality control measures before processing. Compared to subjective evaluation approaches that rely on human observers, automated quality metrics provide reproducible measurements and scalable analysis capabilities for large-scale operational deployment.

However, traditional quality assessment approaches suffer from fundamental limitations when applied to detection-specific requirements. The main limitation is that conventional metrics such as PSNR and SSIM focus primarily on global image characteristics rather than localized quality factors that influence object recognition accuracy. Recent advances in detection-aware quality assessment have emphasized developing specialized metrics that correlate more strongly with detection performance [8].

B. Object Detection and Data Augmentation

Object detection systems consist of interconnected components including feature extraction networks, region proposal mechanisms, and classification modules that work collaboratively to identify and localize objects within images. The detection process operates through multi-stage analysis beginning with convolutional feature extraction, followed by spatial attention mechanisms for object localization, and concluding with categorical classification based on learned feature representations.

Given the constraints of limited training data or insufficient environmental diversity, detection models experience performance degradation due to overfitting and poor generalization capabilities across varying operational conditions [9]. Upon recognizing these limitations, researchers have developed data augmentation techniques to enhance dataset diversity and improve model robustness without requiring additional data collection efforts.

Data augmentation works by applying systematic transformations to existing training images, generating synthetic variations that simulate different environmental conditions, viewing angles, and quality characteristics. The main advantage of augmentation techniques lies in their ability to artificially expand dataset size while introducing controlled variations that improve model generalization across diverse scenarios. Compared to traditional training approaches, augmentation enables detection models to develop robustness against quality degradations that occur in operational environments.

However, data augmentation approaches suffer from limitations that particularly affect defense applications. The main limitation is that conventional augmentation techniques often apply uniform transformations across entire datasets without considering specific quality requirements of different object classes or environmental conditions. Unfortunately, inappropriate parameter selection can introduce artifacts reducing detection accuracy, while lacking systematic quality monitoring hinders optimization for operational requirements.

C. Defense Environment Constraints

Defense operational environments encompass scenarios where data acquisition faces unique constraints that differ significantly from civilian computer vision applications. Environmental factors in defense contexts include strict military security protocols that severely limit access to classified imagery and operational datasets, making comprehensive data collection for research and development purposes extremely challenging. While some operational data remains accessible, it typically exhibits quality polarization, consisting of either low-quality images unsuitable for detection tasks or images that are excessively well-suited for detection, failing to represent realistic operational challenges including nighttime operations, adverse weather conditions, and low-resolution imaging situations.

In scenarios where defense systems attempt to acquire representative training data, researchers encounter systematic quality challenges including severe object class imbalances

where certain target categories have substantially fewer training examples than others, creating model bias problems that require specialized mitigation strategies. The diversity of geographical and environmental conditions encountered in defense operations further complicates data collection efforts, as comprehensive datasets must account for regional variations, seasonal changes, and diverse terrain characteristics essential for operational effectiveness.

However, defense detection systems suffer from the absence of standardized data quality guidelines specifically designed for military operational requirements. The main limitation is that existing quality assessment methodologies developed for civilian applications do not address the unique constraints of defense environments, where detection performance must be maintained across diverse operational scenarios while operating under strict security protocols. This gap between civilian computer vision advances and defense application requirements represents the primary barrier preventing direct adoption of state-of-the-art detection technologies in military contexts, necessitating specialized quality assessment frameworks designed specifically for defense operational constraints.

III. METHODOLOGY

A. A Comprehensive Quality Metrics Framework Design

To systematically address quality assessment challenges in defense object detection applications, we need a comprehensive framework that captures diverse aspects of image characteristics that affect detection performance in military operational scenarios. Our approach systematically organizes 302 established quality metrics across 14 specialized categories, adapting proven quality assessment methodologies from computer vision literature to address unique requirements of defense applications where cost-effectiveness and scenario-based analysis are critical operational considerations.

Defense object detection systems require reliable performance assessment that overcomes limitations of existing global metrics and addresses complexity of diverse operational environments. The framework design philosophy emphasizes comprehensive coverage across all critical quality dimensions that influence object detection performance. Each of the 14 categories serves a specific purpose in the overall assessment process, with categories selected based on their relevance to detection accuracy and their ability to capture distinct aspects of image quality.

Table I presents the comprehensive organization of our 302 metric framework across 14 specialized categories. The framework addresses defense-specific requirements by systematically categorizing established quality metrics into specialized areas that comprehensively evaluate image characteristics critical to object detection performance in military environments. As shown in Table I, the systematic organization progresses from Basic & Global categories (57 metrics total) that provide dataset infrastructure validation, through Fundamental Quality categories (70 metrics total) that assess core image characteristics affecting detection accuracy, to Color Analysis categories (148 metrics total) that enable environmental adaptation

assessment, and finally Structural & Content categories (27 metrics total) that evaluate object-specific detection factors.

The systematic categorization reflects hierarchical nature of image quality assessment in defense applications, progressing from fundamental image properties through global quality measures to object-specific characteristics. The utilization of multiple complementary algorithms within each category addresses complex quality degradation factors that individual metrics cannot capture, providing robust and reliable assessment essential for defense operational environments.

The Sharpness/Edge category employs four distinct algorithms that provide a comprehensive edge quality evaluation. Laplacian Variance measures second-derivative-based sharpness, Energy of Gradient calculates gradient energy distribution, Sum Modified Laplacian provides enhanced edge detection capability and Brenner algorithm evaluates focus quality through adjacent pixel differences. The Contrast category utilizes both Michelson contrast for global characteristics and RMS contrast for local variations essential for object boundary detection under various operational conditions.

B. GPGPU Parallel Processing Architecture

Our system employs GPU-accelerated parallel processing capabilities specifically optimized to achieve comprehensive quality assessment on standard commercial hardware without requiring expensive server infrastructure. The parallel processing architecture implements strategic memory management and data transfer optimization to minimize computational overhead between processing units, addressing the computational challenge of simultaneously executing 302 heterogeneous quality metrics across diverse algorithmic patterns. The system processes image datasets through optimized batch operations that maintain data primarily within GPU memory throughout the quality assessment pipeline, while memory pooling techniques ensure data residency during multi-stage processing phases.

The 302 quality metrics are organized into parallel execution streams that process multiple images simultaneously across different assessment categories. Basic information extraction, quality metric computation, color analysis, and texture evaluation operations execute concurrently across available GPU cores, maximizing computational resource utilization. Upon completion of metric calculations, results are aggregated within GPU memory before final transfer to CPU for analysis and reporting purposes, enabling defense organizations with limited computational budgets to access comprehensive quality analysis capabilities while maintaining performance suitable for operational deployment scenarios.

C. Annotation-Based Data Augmentation Strategy

The augmentation framework utilizes annotation compatibility to enable object-level enhancement strategies specifically designed for defense application training scenarios. Our approach incorporates five core augmentation techniques applied through parallel processing, each addressing distinct operational challenges encountered in defense environments: bright-

TABLE I
QUALITY METRICS ORGANIZATION FRAMEWORK

Category	Metric (Count)	Technical Implementation & Defense Application Focus
Basic & Global	Basic Info (37)	File properties, resolution verification; dataset basic information verification and infrastructure compatibility assessment.
	Overall Quality (20)	Weighted quality indices, global scoring; comprehensive quantitative scoring for images and object classes through multi-metric integration.
Fundamental Quality	Brightness/Exposure (12)	Histogram-based exposure evaluation; operational environment assessment for dawn, dusk, and variable lighting conditions.
	Contrast (20)	Michelson/RMS contrast computation; target-background separability analysis under camouflage and concealment scenarios.
	Sharpness/Edge (16)	Laplacian Variance, EOG, SML, Brenner algorithms; target identification precision and boundary definition capability assessment.
	Focus (12)	Focus mapping, blur detection algorithms; optical system performance validation and image clarity evaluation.
	Noise (10)	SNR computation, noise characterization; sensor reliability assessment under various environmental and operational stress conditions.
Color Analysis	General Color (16)	HSV statistical analysis, saturation metrics; operational environment consideration including sunrise, sunset, regional, and weather characteristics.
	Detailed & Regional (132)	Per-channel statistical computation and 9-region grid-based evaluation; detailed spectral signature analysis and spatial color distribution analysis for camouflage detection and terrain adaptation.
Structural & Content	Texture/Structure (8)	Statistical texture feature, structural metric computation; surface characteristic evaluation for target material identification and background analysis.
	Image Hashes (10)	Perceptual hashing algorithms; augmentation technique effectiveness verification and content integrity validation.
	Object Boundary (4)	Gradient-based sharpness evaluation; object boundary definition quality assessment for precise target localization.
	Object Texture (5)	Internal texture complexity assessment; target-specific texture characteristic analysis for object classification enhancement.

ness adjustment evaluates detection performance under varying illumination conditions addressing dawn and dusk scenarios, Gaussian noise addition simulates sensor variations under electromagnetic interference, rotation transformation applies orientation changes for multi-perspective surveillance, object-specific scaling operations implement annotation-guided scaling for multi-range detection, and salt-and-pepper noise assessment simulates transmission reliability under communication-constrained environments. These augmentation techniques systematically address the data diversity limitations that significantly impact model robustness and generalization capabilities across varying mission requirements. The parallel processing implementation enables simultaneous application of multiple augmentation strategies while preserving detection-relevant quality characteristics, ensuring that enhanced datasets maintain operational relevance for defense modeling applications. This integrated approach provides comprehensive coverage of environmental variations commonly encountered in defense operations while maintaining computational efficiency essential for resource-constrained operational environments.

D. Automated Quality Inspection and Analysis System

The automated reporting system generates a comprehensive analysis designed explicitly for defense data quality

management without requiring specialized expertise in image quality assessment methodologies. The system architecture coordinates four primary processing modules to provide actionable insights for operational decision-making: the metric calculation module processes individual images through the 302 metric framework generating detailed quality profiles, the statistical analysis module organizes assessment results across 14 specialized categories for each object class enabling quantitative evaluation, the visualization module generates comprehensive reports allowing non-expert users to identify specific quality deficiencies through metric-driven analysis.

This integrated approach enables users to develop informed strategies for improving detection model performance by understanding both current dataset limitations and augmentation effectiveness, facilitating proactive quality management and systematic optimization of image datasets before deployment in critical defense applications. The system ensures optimal detection performance under operational constraints while offering specific enhancement strategies for identified quality deficiencies, making comprehensive data quality analysis accessible to defense organizations regardless of technical expertise level and providing scalable performance suitable for operational deployment scenarios.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experimental Configuration and Performance Validation

We performed all experiments on commercial systems to validate scalability across different computational environments: Intel i9-10900K CPU with NVIDIA RTX2080 and AMD Ryzen 5 3500X CPU with NVIDIA RTX3060. Since security considerations make accessing actual defense datasets extremely challenging for academic research, we conducted comprehensive evaluation using the PASCAL VOC 2012 Competition Dataset, which, while a civilian dataset, provides a robust proxy for evaluating our framework's capabilities under conditions analogous to defense operational environments by intrinsically containing complexities such as object occlusion by terrain, diverse object sizes, and varying illumination that directly simulate real-world challenges like camouflage, line-of-sight obstructions, multi-range detection, and fluctuating environmental conditions pertinent to defense operations. Our comprehensive evaluation demonstrates that the framework achieves 101.76 images per second processing throughput on standard commercial hardware, successfully processing the 13,700-image dataset and validating our quality assessment framework under challenging conditions representative of operational scenarios.

B. Quality Assessment Framework Validation

Throughout evaluation across the dataset, we observe that quality-metric distributions demonstrate consistent and interpretable patterns across different environmental conditions. Analysis of the 20 object classes reveals systematic quality variations, with multiple quality dimensions demonstrating measurable differences between object categories.

Our framework computes a comprehensive suite of 302 metrics across 14 specialized categories, generating quality profiles that enable systematic diagnosis of defense-relevant challenges. For focused validation within the scope of this paper, we selected key metrics that serve as direct proxies for critical challenges in defense operations, particularly those related to target detection under camouflage and adverse environmental conditions.

The most critical validation focused on identifying low contrast conditions that simulate camouflage and concealment scenarios fundamental to defense operations. Our analysis revealed concerning results, with a mean contrast score of 0.454 ($\sigma=0.112$) across the dataset, well below operational thresholds and indicating that poor object-background separability represents a widespread and significant quality issue affecting detection performance. Additionally, overall quality assessment revealed that 33.0% of images exhibited challenging detection conditions below the 0.6 threshold, demonstrating the prevalence of detection-challenging scenarios within the dataset.

In contrast to widespread low-contrast issues, our experimental analysis of the PASCAL VOC dataset showed minimal color variation presence (mean score approaching 0.000) and high sharpness performance (mean score 0.938, $\sigma=0.176$),

along with adequate exposure levels (0.761, $\sigma=0.163$) and strong noise characteristics (0.850, $\sigma=0.105$). This quantitative comparison reveals that challenges related to object-background separability are far more critical data quality problems than signal noise or image clarity issues for this dataset, providing essential insight for prioritizing quality enhancement strategies.

RGB channel analysis revealed distinct spectral signatures, while correlation analysis between color channels provided information on environmental adaptation characteristics essential for defense applications. These findings validate that the framework can perform nuanced diagnostic analysis, not merely identifying individual problems but pinpointing the most critical quality degradation factors for a given dataset. The framework successfully demonstrates quantitative quality scoring capabilities for individual images using the 302 metric assessment system, enabling systematic comparison and optimization of image characteristics across different operational scenarios. This capability to prioritize challenges is essential for guiding efficient data enhancement strategies in resource-constrained defense environments, demonstrating the framework's utility as a diagnostic tool for data pre-assessment in defense applications.

V. RELATED WORK

Image quality assessment(IQA) methodologies have attracted significant attention in computer vision research over the past two decades. Wang et al. [5] proposed the Structural Similarity Index (SSIM) to address fundamental limitations of pixel-based metrics such as PSNR and MSE, incorporating human visual perception through luminance, contrast and structural comparisons. Zhang et al. [11] introduced Learned Perceptual Image Patch Similarity (LPIPS), demonstrating that deep neural network features correlate more strongly with human perceptual judgments than traditional mathematical metrics. Mittal et al. [12] developed BRISQUE, a no-reference quality assessment method based on natural scene statistics that evaluates image quality without requiring reference images. However, existing IQA methodologies suffer from fundamental limitations when applied to object detection scenarios. The main limitation is that these approaches primarily assess overall visual quality rather than localized image characteristics that directly influence recognition accuracy.

Defense-specific computer vision systems have attracted significant attention due to unique operational constraints of military environments. Fan et al. [13] presented comprehensive analysis of camouflaged object detection, revealing that conventional datasets inadequately represent complex visual challenges encountered in military scenarios. Li et al. [14] proposed infrared-visible image fusion techniques for robust detection under adverse conditions, highlighting importance of multi-sensor approaches while acknowledging dependency on individual sensor quality. Chen et al. [15] applied deep learning to SAR image classification, demonstrating effectiveness of domain-specific models while noting challenges posed by speckle noise and unique imaging characteristics. However,

defense-oriented computer vision research suffers from critical limitations in addressing data quality requirements. The main limitation is that existing studies focus primarily on algorithmic solutions and model architectures while lacking systematic frameworks for evaluating data quality standards necessary for reliable performance.

GPU-based parallel processing for image analysis has attracted significant attention for accelerating computer vision applications. Owens et al. [16] established foundational principles of General-Purpose GPU computing, demonstrating how massive parallel architectures can accelerate scientific computing beyond traditional graphics processing. Redmon et al. [17] achieved breakthrough performance in real-time object detection through GPU-optimized YOLO architecture, showing how parallel processing enables practical deployment of complex systems. Abadi et al. [18] developed TensorFlow's distributed computing framework, illustrating how modern deep learning systems leverage GPU parallelization for training and inference. However, existing GPU implementations suffer from limitations when applied to comprehensive quality analysis tasks. The main limitation is that current approaches optimize uniform operations rather than coordinating diverse analytical computations that require different computational patterns and memory access strategies.

VI. CONCLUSION

In this paper, we present a comprehensive data quality analysis framework specifically designed for object detection applications in defense environments, addressing the critical gap where existing global quality metrics fail to capture defense-specific challenges. Our work aimed to establish a systematic methodology that enables quantitative diagnosis and analysis of quality problems inherent in datasets for defense applications, moving beyond traditional image quality assessment approaches that inadequately address military operational requirements.

Our evaluation demonstrated that the proposed framework achieves 101.76 images per second processing throughput through GPU-based parallel processing while systematically organizing 302 established quality metrics across 14 specialized categories. We successfully validated diagnostic capabilities of framework by quantitatively identifying defense-relevant challenging conditions, including low-contrast scenarios (mean score 0.441) and high-noise environments affecting 33.0% of evaluated images. The framework enables cost-effective quality assessment using standard commercial hardware, making comprehensive data quality analysis accessible to defense organizations operating under computational budget constraints while providing actionable insights for dataset optimization.

Future research will focus on extending the framework's capabilities to address emerging defense requirements, including integration with specialized sensor systems, real-time quality assessment for operational deployment, and development of automated quality threshold determination based on mission-specific requirements. Although this work establishes a founda-

tional framework for quantitative diagnosis of dataset quality problems in defense environments, validation using actual operating environment imagery remains a critical next step. A key limitation of this study is the reliance on civilian datasets due to security constraints that prevent access to classified defense imagery, which limits direct validation of framework effectiveness in real operational scenarios.

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