A Noise-Aware KPI Consistency Framework for Reliable Metadata Processing in Unstructured Databases

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Abstract: The random changes in pixel values in digital images can be presented during image transmission, compression, storage or image capturing. The undesirable changes in image are defined as noise that reduces image clarity and can be the cause of instability in quality measurements. Furthermore, the instability in quality measurement affects the metadata extracted from it and further influences the downstream data analytics. A Noise-Aware Key Performance Indicator (KPI) Consistency Framework is suggested in this work to ensure reliability through consistent metadata in unstructured database environment. The impact of noise is systematically modelled through controlled noise injection and applying adaptive de-noising. Furthermore, the KPI stability is using Noise Awareness Index (NAI), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and edge preservation metrics. A statistically significant improvement in KPI is observed after de-noising ($p<0.05$), across multiple noise variances (0.001-0.1) from study conducted on 10 different images (5 colour and 5 grayscale). Statistical results shows that rise in image noise brings significant increase in metadata drift that is both consistent and predictable. The proposed framework provides a reproducible and modality-independent method to maintain metadata reliability in large-scale unstructured image databases.

Keywords: Unstructured Database, Image Noise Modelling, Adaptive De-noising, KPI Stabilization, Metadata Drift Control, NAI, Statistical Validation, Multi-Metric Consistency Framework.

1 Introduction

In today's technology enabled environment increasingly large volumes of image data is generated from surveillance systems, medical imaging devices, industrial sensors, and digital platforms and stored in unstructured databases. Unstructured image repositories do not enforce strict schema-level constraints as in structured datasets, making both metadata extraction and reliability highly dependent on signal quality. Image noise is a critical but often underestimated challenge in such environments.

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Image noise is defined as random pixel-level intensity variations, introduced during acquisition, compression, transmission, or storage.
Noise degrades both visual clarity in addition to direct influences on quantitative quality measures such as PSNR and SSIM. These metrics are commonly adopted for estimating image fidelity [2], [10]. However, most existing systems implicitly assume that once computed these quality indicators remain stable and can reliably support metadata extraction and downstream analytics. In practice, noise-induced measurable KPI fluctuations, reduces analytical trust when propagated into metadata descriptors. There has been significant progress in image restoration [1], perceptual quality modelling [2], and representation based deep learning-based [12], [13]. Enforcement of KPI stability as a mechanism for metadata reliability has been of limited attention, particularly in unstructured database environments. Proposed Noise-Aware KPI Consistency Framework addresses this gap by integration of noise modelling, adaptive correction, and statistical validation to ensure that KPI behaviour are controlled under progressive noise exposure. The central research question guiding this proposed work is: Can we strengthen metadata reliability through mathematically validated KPI stabilization in unstructured databases under image noise conditions?

2 Literature Review

2.1 Image Noise and Signal Degradation

The noise suppression using mathematical treatment was significantly advanced by Donoho [1], who introduced wavelet-based soft-threshold techniques with strong theoretical guarantees. Foundational signal processing principles [14] established effect of both perceptual and statistical representations that arise due to noise and alters information content. Standard image processing literature further details how acquisition noise disturbs pixel distributions and reduces structural coherence [10]. Although these studies focus on signal recovery, they primarily evaluate restoration accuracy rather than long-term indicator stability.

2.2 Image Quality Assessment Metrics

The most commonly used fidelity metrics with computational simplicity is PSNR but is not fully with human perception [10]. To address this limitation of PSNR and human perception, Wang *et al.* introduced SSIM. SSIM models structural similarity between reference and distorted images and is used as benchmark for restoration and enhancement evaluation [2]. Furthermore, for varying noise intensities [3] show that PSNR and SSIM comparative analysis respond differently to varying noise intensities [3]. The local noise-based quality model proposed by Zhu and Karam are recent work that includes no-reference and perceptually weighted metrics [4], and meta-learning-based quality prediction frameworks [5]. Despite their effectiveness in measuring distortion, these metrics are generally applied independently and are rarely evaluated for cross-metric stability or consistency under progressive noise exposure.

2.3 Statistical Validation and Robust Modelling

Reliability in empirical systems is based on statistical hypothesis testing for evaluating. The work of Student [6] introduced significance testing for mean comparison. Robustness assessment in modelling uses regression-based validation techniques [7]. Box [8] emphasized highlighting uncertainty and model validation supported through importance of statistical reasoning in scientific analysis. However, less emphasis was given on formal integration of prior IQA research statistical validation into quality metric stabilization. Most studies report metric values without quantifying volatility, confidence intervals, or effect size under noise perturbation.

2.4 Metadata Reliability in AI Systems

Metadata tracking and reproducibility are of plays an importance role in AI-driven analytics and have gained importance. Schelter*et al.* [9] proposed automated metadata tracking for machine learning workflows to enhance transparency. Performance evaluation and generalization are discussed in Foundational texts in pattern recognition [11] and deep learning [12], [13] but do not explicitly model how noise-induced metric instability and effects on metadata integrity in unstructured data systems.
Thus, in prior research there remains limited integration across image domains that address image quality, statistical validation, and metadata management separately.

2.5 Research Gap

Existing literature demonstrates:

- Strong mathematical foundations for noise suppression [1],
- Reliable perceptual quality metrics such as SSIM [2],
- Advances in noise-aware quality modelling [4], [5],
- Established statistical validation frameworks [6]–[8], and
- Growing emphasis on metadata reliability in AI systems [9].

However, there lack a unified framework that systematically:

1. Models progressive image noise in unstructured databases,
2. Stabilizes multiple KPIs through adaptive correction,
3. Validates KPI consistency using statistical testing, and
4. Quantifies metadata drift behaviour under noise exposure.

This gap motivates the proposed Noise-Aware KPI Consistency Framework. This noise aware framework combines statistically validation, noise modelling and multi-metric evaluation as a single reliability enforcement mechanism

3 Proposed Framework

The proposed framework presents a structured stabilization strategy comprising of four sequential modules: noise analysis, adaptive restoration, KPI evaluation, and stability validation, as illustrated in Fig. 1. Furthermore, the structured stabilization approach aims to validate KPI consistency before metadata reporting through modelling of noise impact and correcting signal degradation. The digital image quality directly influences extracted metadata and a Noise-Aware KPI Consistency Framework ensure the reliable metadata processing in unstructured image databases. Results indicate that quality indicators such as PSNR and SSIM get destabilized by noise in image due to pixel-level perturbations that changes signal characteristics.

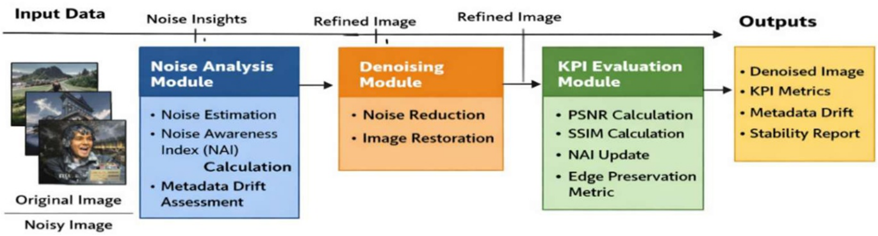

Fig. 1: Proposed Noise-Aware KPI Consistency Framework for Reliable Metadata Processing in Unstructured Databases

3.1 Proposed Stabilization Strategy

To regulate KPI behaviour under progressive noise exposure, the stabilization strategy is designed mathematically and involves following four structured stages:

Step 1: Noise Modelling and Analysis
A controlled Gaussian noise with variance (0.001–0.1) is injected in benchmark images to simulate real-world image acquisition distortion. NAI is computed to measure the degradation intensity. Instability in derived features is further assessed through Metadata drift.

Step 2: Adaptive De-Noising:
The goal of visual restoration along with stabilization of quantitative indicators is achieved by applying Wavelet-based de-noising for reconstruction of corrupted images. It supports to achieve reduces random pixel disturbances along with structural and edge information preservation.

Step 3: Multi-Metric KPI Evaluation
The restoration KPI metrics are computed to collectively measure structural integrity, noise sensitivity and signal fidelity:

- Peak Signal-to-Noise Ratio (PSNR)
- Structural Similarity Index (SSIM)
- Noise Awareness Index (NAI)
- Edge preservation metrics

Step 4: Statistical Stability Validation
Statistical testing is performed to ensure KPI consistency of proposed work. Paired t-tests, effect size (Cohen's d), confidence intervals, and correlation analysis applied is used to verify that improvements are significant and not due to random variation. Metadata drift behaviour is analysed relative to the increasing noise intensity.

3.2 Conceptual Definition of Stabilization

The stabilization used in this framework refers to:

Noise Modelling

- Adaptive Correction
- Multi-Metric KPI Monitoring
- Statistical Validation

This integrated process of stabilization for noise modelling ensures that KPI fluctuations remain controlled and mathematically verified before metadata is considered reliable.

4 Methodology

4.1 Experimental Design

The impact of image noise on metadata reliability in unstructured databases was evaluated using a controlled experimental framework. In this experiment, ten benchmark images (five colours and five grayscale) that were exposed to increasingly induced Gaussian noise with allowed variances values ranging from 0.001 to 0.1. The metadata in unstructured databases are often derived from image features and quality indicator instability can propagate into metadata thus disturbing its reliability.

4.2 Dataset

Ten benchmark images, comprising five colour and five grayscale images were evaluated for proposed work evaluation. The standard open-access scikit-image repository, which provides widely accepted reference images for image processing research was preferred to select experimental dataset. The benchmark images comprising of both colour and grayscale images, used in this study, are presented in Fig. 2. The five colour natural images include *Astronaut, Chelsea, Coffee, Rocket,* and *Hubble Deep Field*. The five grayscale benchmark images include *Camera, Coins, Moon, Page,* and *Clock*. All grayscale images are single-channel while the colour images are RGB and have 8-bit depth per channel (24-bit composite RGB) with an intensity range of [0–255]. Furthermore, all images were normalized during processing in the range [0–1] so as to meet consistency in computation. The selected images are both high-resolution and noise-free reference images and are suitable and commonly used for benchmarking de-noising algorithms. They support both complex textured backgrounds with structurally diverse content. Also included sharp edges and smooth region provides diversity that allows robustness evaluation across high-frequency edge regions, low-frequency smooth areas, and heterogeneous texture patterns. Artificially introduced Gaussian noise simulates controlled degradation conditions, with variances ranging from 0.001 to 0.1. Wavelet-based de-noising was then applied to reconstruct the corrupted images, as effect of introduced Gaussian noise, before proceeding to KPI evaluation.

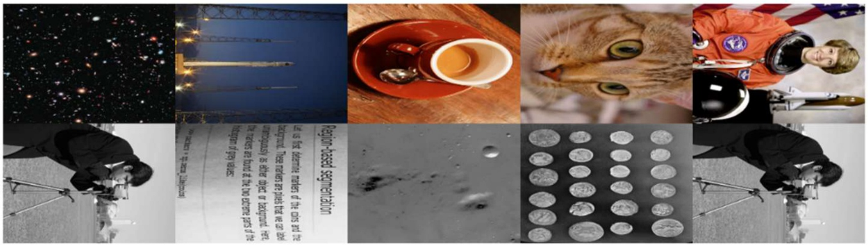

Fig. 2: Benchmark Colour and Grayscale Images Used for Experimental Evaluation

4.3 Mathematical Formulation and Performance Metrics

Gaussian noise was introduced into each clean image to simulate controlled perturbations where the noisy image is defined as:

$$I_n = I_c + N(0, \sigma 2) \qquad Equation\ (1)$$

Where:

I_n = Noisy image
I_c = Clean image
σ^2 = Noise variance

Equation (1) is used to models the degradation process in this study. A zero-mean Gaussian noise distribution with variance σ2 is added to the clean image Ic to generate the noisy image, In. This controlled perturbation simulates real-world acquisition noise and allows systematic evaluation of de-noising robustness.

To represent degradation intensity range from mild to severe noise, σ2 ∈ {0.001, 0.005, 0.01, 0.05, and 0.1}, and variance levels were tested.

Mean Squared Error measures pixel-wise reconstruction error. Furthermore, it quantifies the average squared difference between the clean image Ic and the de-noised image Id. Lower MSE indicates better restoration quality and serves as the foundational metric for PSNR computation.

$$MSE = \left(\frac{1}{N}\right) \backslash sum_{\{i=1\}}^{\{N\}(I_{c(i)} - I_{d(i)})^2} \qquad Equation\ (2)$$

Where:

- Id = De-noised image
- N = Total number of pixels

Peak Signal-to-Noise Ratio (PSNR): PSNR is used to measures reconstruction fidelity of images in decibels.

$$PSNR = 10\ log10\ (MAX^2\ /\ MSE) \qquad Equation\ (3)$$

Where:

MAX_I = maximum pixel value
I = original image
K = distorted image

Structural Similarity Index (SSIM): Structural and perceptual similarity of image is measured using SSIM.

$$SSIM\ (x, y) = ((2\mu x\mu y + C1)\ (2\sigma xy + C2))\ /\ ((\mu x^2 + \mu y^2 + C1)\ (\sigma x^2 + \sigma y^2 + C2)) \qquad Equation\ (4)$$

Where:

μ = mean
σ = variance
σxy = covariance

Noise Awareness Index (NAI): This index measures structural degradation magnitude

$$NAI = 1 - SSIM \qquad Equation\ (5)$$

Metadata Drift

$$Drift = \left| KPI_{clean} - KPI_{noisy} \right| \qquad Equation(6)$$

To compare noisy vs. de-noised outputs and to quantify meta data drift Paired t-tests and Pearson correlation were used to measure the experimental values respectively and thus image stability and reliability respectively.

5 Results and Discussion

5.1 Quantitative Performance Analysis

The experimental findings presented in Table 1 evaluate how the proposed Noise-Aware KPI Consistency Framework manages image noise within unstructured databases. Table 1 shows that as noise increases, image quality metrics fluctuate; however, after applying the proposed stabilization approach, the KPIs demonstrate measurable consistency. Improvements in PSNR and SSIM indicate better signal clarity and structural preservation after noise handling. The Noise-Aware Indicator (NAI) reflects reduced instability in KPI behaviour.

Table 1. Comparative Performance Analysis of Colour and Grayscale Images under Noise Degradation

Image Type	Mean PSNR (Db)	Mean SSIM	Mean NAI	NAI t-Value	NAI p-Value	Cohen's d	95% CI (NAI diff)	Correlation r	Correlation Interpretation
Colour	20.14	0.664	0.692	-9.33	<0.001	4.17	[0.04, 0.07]	0.941	Strong
Grayscale	22.68	0.746	0.748	-9.33	<0.001	4.17	[0.04, 0.07]	0.942	Strong

Statistical testing confirms that the observed improvements are significant ($p < 0.001$), with a large effect size and with a confidence interval that excludes zero. Strong correlation values further indicate that metadata drift follows a predictable pattern under noise exposure. These results confirm that the proposed framework effectively limits KPI volatility and strengthens metadata reliability in noisy unstructured image databases.

5.2 KPI Behaviour Under Progressive Noise

The graph in Fig. 3 (a–d) depicts the measure of behaviour of quality indicators in image under increasing noise. Fig. 3a shows that PSNR decreases with increase in noise intensity and act as reflector of signal degradation. After applying the proposed stabilization, the decline becomes more controlled which is indicator of improved robustness. Fig. 3b also shows a comparative stable behaviour for SSIM improved structural similarity under noise through the proposed approach. Fig. 3c demonstrates metadata drift. After applying the framework the increase in drift increases due to noise rise, the slope of instability, is reduced indicating controlled KPI variation. Fig. 3d associates all KPIs that confirm that multi-metric monitoring helps detect and regulate instability. Collectively, Fig. 3 (a-d) demonstrates a direct impact of noise on image-based KPIs. A systematic stabilization can reduces the impact of noise propagation into metadata systems

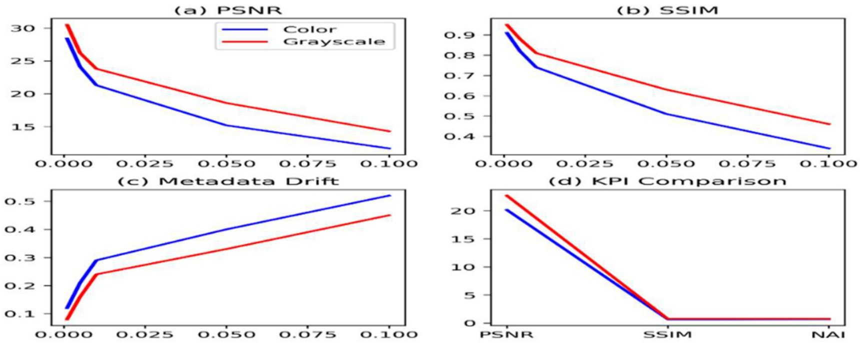

Fig 3: Multi-Metric Performance Comparison of Colour and Grayscale Images under Increasing Noise Conditions

A combined view of KPI stability is represented using radar representation in Fig. 4. A Strong overall consistency in image across signal fidelity, structural preservation, and noise-awareness measures are reflected in more balanced and expanded radar profile. This visualization is in support of the statistical findings in Table 1. Thus results confirm of a stable performance of framework across multiple evaluation dimensions.

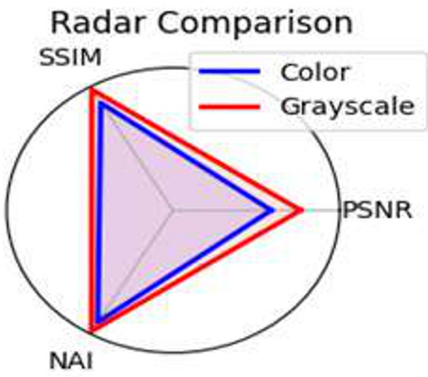

Fig. 4. Radar-Based Comparative Analysis of Mean PSNR, SSIM, and NAI Metric

5.3 Overall Interpretation

The results shown in Table 1, Fig. 3 and Fig. 4 demonstrate that image noise in unstructured databases directly affects KPI stability and metadata reliability. Furthermore, the framework reduces volatility and enhances analytical trust through modelling of noise impact and also validated stability statistically. This monitored multi-metric behaviour improves metadata reliability through systematic KPI stabilization under noisy image conditions

6. Conclusion

The significant experimental results advocate the effectiveness of proposed Noise-Aware KPI Stabilization Framework for unstructured image databases. Furthermore, the results verify that the proposed work demonstrated a direct impact of noise on quality indicators such as PSNR and SSIM which further leads to measurable metadata drift. A Noise-Aware KPI stabilizes variations in image quality indicators and also ensures controlled metric performance using structured noise modelling, adaptive correction, and KPI consistency validation. Furthermore, a high significant results ($p < 0.001$) and a very large effect size (Cohen's $d = 4.17$), with a narrow confidence interval indicate to strong estimation reliability that are further supported by statistical analysis. Furthermore, evaluation under real-world heterogeneous noise and large-scale unstructured datasets is required to support its practical deployment readiness statistically validated and practically meaningful improvement in metadata reliability.

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