INSTITUTE FOR INFORMATICS AND AUTOMATION PROBLEMS OF THE NAS RA

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OPTIMIZING IMAGE PROCESSING METHODS WITH APPLICATIONS

ABSTRACT

of the dissertation for obtaining a Ph.D. degree in Technical Sciences on specialty 05.13.05 “Mathematical modelling, numerical methods and program complexes”

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ՀՀ ԳԱԱ ԻՆՖՈՐՄԱՏԻԿԱՅԻ ԵՎ ԱՎՏՈՄԱՏԱՑՄԱՆ ՊՐՈԲԼԵՄՆԵՐԻ ԻՆՍՏԻՏՈՒՏ

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Երևան 2025

Ատենախոսության թեման հաստատվել է ՀՀ ԳԱԱ Ինֆորմատիկայի և ավտոմատացման պրոբլեմների ինստիտուտում:

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Առաջատար կազմակերպություն՝

Մասնագիտացված խորհրդի գիտական քարտուղար ֆ. մ. գ. դոկտոր՝ Մ. Ե. Հարությունյան

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General Description of the Work

Relevance of the Research

The rapid adoption of solar photovoltaic (PV) technology as a cornerstone of the global renewable energy transition has introduced technical challenges in ensuring long-term reliability and efficiency. Defects such as micro-cracks, interconnect corrosion, and thermal hotspots can significantly reduce energy yield, making early detection imperative. Thermal imaging has emerged as a vital diagnostic tool due to its ability to detect infrared radiation indicative of such faults. However, the inherent limitations of thermal imagery, low contrast, limited resolution, and high noise sensitivity, pose significant barriers to robust automated analysis.

This dissertation is driven by the need for data-efficient, computationally lightweight, and thermally adapted image processing techniques for defect detection in PV systems. Manual inspection is impractical at scale, and conventional methods developed for visible-spectrum images are often inadequate for thermal modalities. The proposed research fills this gap by advancing a quality-aware processing pipeline that integrates image enhancement, augmentation, and classification tailored to the unique properties of thermal data.

One of the core motivations is the absence of perceptually relevant, no-reference image quality metrics for specialized imaging tasks. In our work on image decolorization, we developed the TIA and WTIA metrics—non-parametric, robust measures that accurately quantify contrast preservation without relying on subjective thresholds [1]. These metrics offer substantial improvements over traditional methods like CCPR and E-score, enabling optimal grayscale conversion with minimal distortion of salient regions.

In the thermal domain, we introduced a novel entropy metric, Block-wise Image Entropy (BIE), which combines global statistical behavior with local structure preservation. This metric enhances quality assessment in thermal images, allowing for more accurate visibility enhancement and noise mitigation. Moreover, BIE serves as an optimization target in parameter tuning frameworks powered by genetic and bat algorithms, yielding superior contrast enhancement results validated across multiple thermal datasets [2].

Building on this foundation, we proposed a novel augmentation strategy using BIE-guided contrast optimization to generate high-quality synthetic samples for training classification networks. This augmentation method significantly improves model performance in low-data regimes, outperforming standard techniques such as geometric transforms and histogram equalization. Experiments with PV module defect datasets showed consistent accuracy and robustness gains across a range of deep learning models, including CNN and Transformer architectures [3].

Finally, to enable scalable deployment in resource-constrained settings, such as

UAV-based inspections, we designed *SlantNet*, a lightweight neural network incorporating slant harmonic convolutions. This architecture preserves critical frequency information while minimizing computational load, achieving competitive classification results on small, low-resolution thermal images [4].

In summary, this dissertation presents an end-to-end framework for optimizing thermal image processing, from quality assessment and enhancement to data augmentation and classification. The methods proposed are not only domain-aware and data-efficient but also adaptable to broader applications, including wind turbine inspection, transformer monitoring, and medical thermography. This work offers a significant step toward scalable, intelligent, and energy-aware fault analysis solutions.

Aim of the Work and Key Objectives

The aim of the work is to develop an end-to-end, resource-efficient image processing pipeline that boosts the accuracy and reliability of thermal/infrared defect detection,particularly for solar PV inspection,while remaining deployable on low-power devices.

To achieve this goal, the research is structured around the following key objectives and tasks:

1. Develop robust no-reference quality metrics to evaluate and optimize color-to-grayscale conversion. The proposed metrics, Threshold-Independent Area (TIA) and its weighted variant WTIA, ensure perceptual structure preservation during preprocessing and enable data-driven decolorization without relying on reference images.
2. Design an entropy-based contrast enhancement framework tailored for thermal infrared imagery. The method integrates a novel uncertainty quantification term to guide adaptive parameter selection, effectively suppressing noise and enhancing subtle thermal patterns that are critical for accurate diagnostics.
3. Implement a metric-guided data augmentation strategy to enrich thermal image datasets. This includes generating high-quality synthetic samples based on contrast and entropy metrics, prioritizing augmentation of underrepresented classes and rare fault types to improve model generalization under data-constrained conditions.
4. Propose a compact and efficient neural network architecture, SlantNet, that incorporates harmonic slant convolutions for spatial-frequency representation. The model achieves strong classification accuracy on low-resolution thermal data while minimizing computational cost, making it ideal for deployment on drones, embedded systems, and other edge devices.
5. Integrate all components into a unified processing pipeline and benchmark it against state-of-the-art methods. The system is evaluated on multiple datasets,

including those from solar PV modules, wind turbines, and industrial equipment. To foster reproducibility and community use, an open-source implementation is made publicly available.

Research Objects / Subject of the Research

The object of this research is thermal and infrared imaging data used for defect detection and classification in renewable energy systems and industrial inspection. Specifically, the study focuses on thermal images of photovoltaic (PV) modules, wind turbine blades, and electrical equipment such as transformers and motors, emphasizing low-resolution, noise-prone imagery acquired under real-world conditions, particularly from UAVs and embedded systems. The subject of the research is the development of an integrated, quality-aware image processing framework tailored to thermal data. This includes designing no-reference image quality assessment metrics for grayscale conversion, entropy-based contrast enhancement methods incorporating uncertainty quantification, and data augmentation techniques driven by thermal-specific quality measures. Additionally, the research investigates lightweight neural network architectures such as SlantNet that combine computational efficiency with strong classification accuracy. The methods are evaluated across multiple thermal datasets to demonstrate improvements in model robustness, interpretability, and deployability in constrained environments. Together, these components form a cohesive pipeline for intelligent, automated inspection in solar energy and related domains.

Research Methods

The research methodology is grounded in analytical modeling, algorithmic development, experimental validation, and comparative evaluation. First, theoretical foundations were established for novel image quality metrics, Threshold-Independent Area (TIA), its weighted variant WTIA, and Block-wise Image Entropy (BIE), designed for no-reference assessment of grayscale conversion and thermal image contrast. These metrics were derived from principles of information theory, human visual perception, and structural image statistics. Optimization techniques such as genetic algorithms and the bat algorithm were employed to automatically tune enhancement parameters for thermal images, using the proposed metrics as objective functions. For data augmentation, a metric-guided oversampling method was implemented, where thermal images were enhanced and selected based on their BIE scores to ensure high-quality synthetic training samples. Deep learning methods were applied to design and train lightweight convolutional neural networks, most notably SlantNet, featuring harmonic slant convolutions for efficient classification of low-resolution thermal images. The performance of all proposed methods was assessed through extensive experiments using publicly available and custom thermal datasets from PV modules, wind turbines, and industrial systems. Evaluation metrics included accuracy, precision, recall, specificity, and runtime efficiency, benchmarked against state-of-the-art enhancement and classification techniques to validate the effectiveness and practical viability of the proposed framework.

Scientific Novelty of the Work

The scientific contributions and novelties of this research are summarized as follows:

- A new class of no-reference quality metrics, Threshold-Independent Area (TIA) and its weighted variant WTIA, are proposed for evaluating grayscale image quality without requiring ground-truth references or parameter tuning, ensuring robust perceptual structure preservation during decolorization.
- A novel entropy-based metric, Block-wise Image Entropy (BIE), is introduced for thermal image quality assessment. It effectively captures both local and global contrast variations, enabling accurate contrast enhancement while suppressing noise in thermal imagery.
- For the first time, thermal image enhancement is formulated as an optimization problem where image quality metrics (TIA, BIE) serve as objective functions in evolutionary algorithms, including genetic and bat algorithms, for adaptive parameter tuning.
- A metric-guided data augmentation framework is proposed, generating high-quality synthetic thermal images by selectively enhancing contrast and entropy, thereby improving model generalization in low-data or imbalanced scenarios.
- A new lightweight neural network architecture, SlantNet, is developed, incorporating harmonic slant convolutions to achieve high thermal classification accuracy with significantly reduced computational complexity, suitable for real-time edge deployment.
- The proposed methods are integrated into a quality-aware pipeline primarily applied to thermal PV module datasets for fault classification, with additional experiments conducted on other thermal datasets, such as pedestrian and vehicle detection or wind turbine inspection, to evaluate generalizability in enhancement and classification tasks.

Practical Significance of the Work

The results of this research have direct applicability in the development of efficient and scalable solutions for automated thermal inspection in real-world environments. The proposed image quality metrics, enhancement techniques, and lightweight classification models are specifically designed to operate under resource constraints, making them highly suitable for deployment on embedded devices, UAV platforms, and edge-based monitoring systems. This enables real-time fault detection in photovoltaic (PV) modules, reducing inspection costs, minimizing downtime, and improving long-term energy output.

Moreover, the developed methods contribute to the broader field of thermal image analysis by offering tools that enhance contrast, quantify uncertainty, and guide data augmentation in a quality-aware manner. These contributions extend beyond solar energy applications, demonstrating effectiveness in other thermal domains such as pedestrian and vehicle detection in surveillance, as well as industrial equipment monitoring. The open-source release of key components encourages reproducibility and adoption by both academic researchers and industry practitioners seeking robust, interpretable, and efficient thermal imaging solutions.

Publications

The results of the dissertation have been published in 4 scientific articles, 3 of which are indexed in international databases such as Web of Science and Scopus. The full list of publications is provided at the end of the abstract.

Scope and Structure of the Dissertation

The dissertation consists of 115 pages, including an introduction, four chapters, a conclusion, and an appendix. It contains 132 bibliographic references and incorporates both theoretical developments and experimental results based on real thermal datasets.

Content of the Dissertation

Introduction is the first chapter of the dissertation and presents the motivation, research context, problem formulation, and overall structure of the work.

In Chapter 2, the proposed threshold-independent quality assessment framework for image decolorization is presented. The chapter introduces novel evaluation metrics designed to address the limitations of existing methods, particularly their reliance on user-defined thresholds and lack of alignment with human perception.

Section 2.1 introduces the problem of image decolorization, highlighting the importance of preserving color contrast and structural content during grayscale conversion. It motivates the need for robust no-reference quality metrics, especially in applications where no ground-truth grayscale reference is available. The challenge lies in designing evaluation methods that account for perceptual contrast loss and structural degradation, without depending on subjective human feedback.

Section 2.2 provides an in-depth review of related work. Traditional grayscale conversion techniques apply fixed linear combinations of RGB values, such as:

$$g = aR + bG + cB, \tag{1}$$

where a, b, and c are fixed weights, e.g., in the Luminosity method $g = 0.21R + 0.72G + 0.07B$. While computationally efficient, these approaches often fail to preserve chromatic contrast and perceptual salience (see Fig. 1).

More sophisticated methods include chrominance-aware techniques (e.g., Bala et

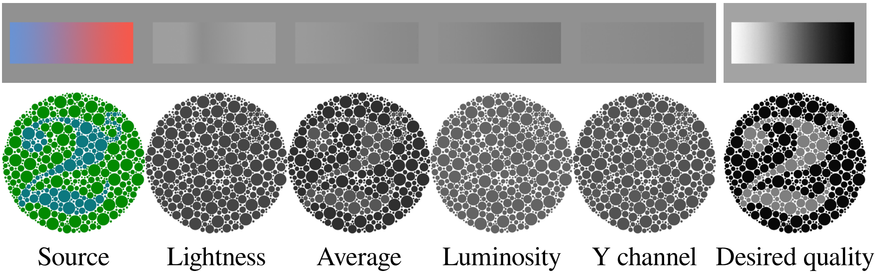

Figure 1: Comparison of linear grayscale conversion methods. Decolorized images can lose the contrast and become hardly visible.

al.) and energy minimization approaches (e.g., Rasche, Neumann), which attempt to retain color edges or adapt the grayscale output based on visual models. Neural network-based methods also emerged, using saliency cues and deep representations to improve decolorization.

As for evaluation, existing no-reference metrics include the Color Contrast Preserving Ratio (CCPR) and Color Content Fidelity Ratio (CCFR). Combined, they form the E-score:

$$\text{E-score} = \frac{2 \cdot \text{CCPR} \cdot \text{CCFR}}{\text{CCPR} + \text{CCFR}}, \tag{2}$$

where

$$\text{CCPR} = \frac{\#(x, y)|(x, y) \in \Omega, |g_x - g_y| \geq \tau}{||\Omega||}, \tag{3}$$

$$\text{CCFR} = 1 - \frac{\#(x, y)|(x, y) \in \Theta, \delta_{x,y} \leq \tau}{||\Theta||}, \tag{4}$$

with $\delta_{x,y}$ as the CIE LAB color difference. These metrics depend heavily on a user-defined threshold τ, leading to inconsistent evaluations across different methods and datasets. Additionally, they fail to account for spatial saliency and do not generalize well across varying image content (Table 1).

Section 2.3 presents the proposed quality metrics: Threshold-Independent Area (TIA) and its weighted variant (WTIA). TIA addresses the instability of τ-dependent metrics by analyzing the E-score curve across multiple thresholds ($\tau = 2 \ldots 10$) and computing the area under a fitted regression line:

$$\text{TIA} = \max\left(\frac{2\alpha + \beta}{2}, 0\right), \tag{5}$$

where α and β are the slope and intercept of the line $y = \alpha + \beta x$ approximating the

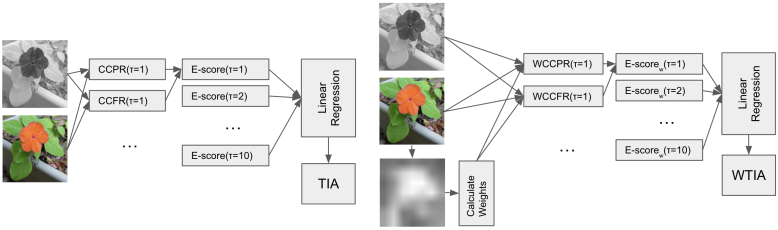

Figure 2: Workflow for proposed quality metrics: An overview of the sequential steps and stages involved in calculating the TIA and WTIA quality metrics

E-score curve.

To better align with perceptual importance, WTIA incorporates visual attention using weighted E-score components:

$$\text{E-score}_w = \frac{2 \cdot \text{WCCPR} \cdot \text{WCCFR}}{\text{WCCPR} + \text{WCCFR}}, \tag{6}$$

where weights w_x, w_y are derived from saliency maps:

$$\text{WCCPR} = \frac{\sum w_x w_y |(x, y) \in \Omega, |g_x - g_y| \geq \tau}{\sum w_x w_y |(x, y) \in \Omega}, \tag{7}$$

$$\text{WCCFR} = 1 - \frac{\sum w_x w_y |(x, y) \in \Theta, \delta x, y \leq \tau}{\sum w_x w_y |(x, y) \in \Theta}. \tag{8}$$

This modification ensures that regions more important to human perception are emphasized, enhancing metric reliability. The full pipeline is illustrated in Fig. 2.

Section 2.4 describes simulation studies validating the effectiveness of TIA and WTIA. Using Ĉadík and COLOR250 datasets, correlation with human ratings was assessed using the Kendall rank coefficient R:

$$R = \frac{\#\{\text{concordant pair}\} - \#\{\text{disconcordant pair}\}}{\frac{1}{2}n(n-1)}, \tag{9}$$

TIA and WTIA showed significantly higher R values than E-score and its components, validating their perceptual alignment. As we can see in Table 1, the proposed metrics achieve the highest correlation with both accuracy and preference scores, confirming their superiority in reflecting human judgment. Furthermore, a genetic algorithm was

Table 1: Average Kendall correlation rank between metrics and user scores on Čadík's dataset (C) and the subset of it (C')

Metric	Accuracy		Preference	
	C	C'	C	C'
$\text{CCPR}_{\tau=4}$	0.2341	0.2971	0.2222	0.2698
$\text{CCPR}_{\tau=5}$	0.2341	0.2925	0.2222	0.2562
$\text{CCPR}_{\tau=6}$	0.2222	0.2834	0.2183	0.2472
$\text{CCFR}_{\tau=4}$	0.2430	0.2210	0.2953	0.2763
$\text{CCFR}_{\tau=5}$	0.1950	0.2025	0.2626	0.2479
$\text{CCFR}_{\tau=6}$	0.2586	0.2616	0.3180	0.2977
$\text{E-score}_{\tau=3}$	0.4167	0.4376	0.4603	0.4558
$\text{E-score}_{\tau=4}$	0.4405	0.4603	0.4762	0.4785
$\text{E-score}_{\tau=5}$	0.4365	0.4512	0.4563	0.4603
$\text{E-score}_{\tau=6}$	0.4206	0.4376	0.4484	0.4467
$\text{E-score}_{\tau=7}$	0.4206	0.4376	0.4563	0.4558
TIS	0.1905	0.2517	0.2024	0.2245
TIA	**0.4563**	**0.4785**	**0.4841**	**0.4875**
WTIA	**0.4802**	**0.5011**	**0.4921**	**0.5011**

applied to solve:

$$\max_{a,b,c} F(a,b,c), \tag{10}$$

where F is TIA or WTIA, and a, b, c are grayscale weights. This optimization yielded content-adaptive grayscale conversions that outperformed traditional fixed-weight approaches.

Section 2.5 concludes the chapter by summarizing the key contributions. TIA and WTIA provide robust, threshold-free, and perceptually aligned evaluation tools for grayscale conversion. Their integration into optimization frameworks enables high-quality, adaptive decolorization across diverse applications, overcoming limitations of prior methods and advancing the field of image quality assessment.

In Chapter 3, the focus shifts to thermal imaging, where a novel entropy-based no-reference Image Quality Assessment (IQA) metric is proposed, aimed at addressing the limitations of existing enhancement and uncertainty quantification methods in infrared images. This chapter introduces Block-wise Image Entropy (BIE), a hybrid metric that combines local structural analysis with global contrast cues to evaluate and optimize the quality of thermal images under challenging conditions.

Section 3.1 introduces the role of thermal imaging across fields such as medicine, building diagnostics, and industrial maintenance, emphasizing the difficulty of processing noisy and low-contrast infrared images. It discusses how uncertainties, stemming from sensor noise, environmental influences, and the complex physics of heat transfer, lead to image artifacts and analysis errors. Despite the broad application of thermal imaging, traditional tools for uncertainty quantification remain underdeveloped. Quality metrics, particularly entropy-based approaches, are central to image evaluation and enhancement. However, conventional formulations fall short in thermal contexts. These limitations motivate the need for a new formulation that can more reliably assess the informational content of thermal images.

Section 3.2 reviews existing entropy-based and block-wise metrics. Shannon entropy,

$$E(I) = -\sum_{i=1}^{N} P(i) \log_2 P(i), \tag{11}$$

measures the global uncertainty of pixel intensity distribution, where $P(i)$ is the probability of the i-th intensity level, and N is the number of possible intensity levels. Rényi entropy,

$$R_\alpha(I) = \frac{1}{1-\alpha} \log_2 \left(\sum_{i=1}^{N} P(i)^\alpha \right), \tag{12}$$

generalizes this with a parameter α that adjusts sensitivity to pixel probability concentrations. Yet both fail to capture spatial structure and are prone to noise. Block-based metrics like EME and AME offer localized evaluations:

$$EME(I) = \frac{1}{n} \sum_{k=1}^{n} \left(20 \ln \frac{I_{\text{max}}^k}{I_{\text{min}}^k + c} \right), \tag{13}$$

$$AME(I) = \frac{1}{n} \sum_{k=1}^{n} \alpha M(I^k)^\alpha \ln M(I^k), \quad M(I^k) = \frac{I_{\text{max}} - I_{\text{min}}}{I_{\text{max}} + I_{\text{min}} + c}, \tag{14}$$

where n is the number of blocks, I_{max}^k and I_{min}^k are maximum and minimum intensities in block k, and c is a small constant to prevent division by zero. These metrics are often misled by noise, overstating quality in degraded images.

Section 3.3 introduces the Block-wise Image Entropy (BIE) metric, which integrates global contrast, block-wise entropy, and structural consistency. It is defined as:

$$BIE(I) = ADP(I) \times \frac{\frac{1}{n}\sum_{k=1}^{n} (\alpha M'(I^k)^\alpha \ln M'(I^k))}{1 + \frac{1}{n}\sum_{k=1}^{n} E(I_k)} \times \frac{SD(I)}{1 + \frac{1}{n}\sum_{k=1}^{n} SD(I_k)}, \tag{15}$$

where $M'(I^k)$ is the normalized modulation of block I^k, $E(I_k)$ is its Shannon entropy, and $SD(I)$ is standard deviation. The term $ADP(I)$ captures average deviation

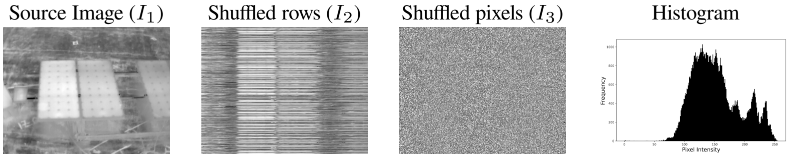

Figure 3: Thermal image and intentionally distorted versions with identical histogram distributions.

Table 2: Entropy-based metric values for images depicted in Figure 3.

Image	E	R2	SD	EME*	AME*	BIE*
I_1	7.202	4.868	39.89	9.892	0.289	**0.114**
I_2	7.202	4.868	39.89	18.12	**0.345**	0.045
I_3	7.202	4.868	39.89	**28.63**	0.315	0.027

* All block-based measures are calculated using $block\_size = 15$ parameter value.

percentage:

$$ADP(I) = 1 - \frac{|A(I) - L/2|}{L/2}, \quad M'(I^k) = \frac{I_{\max} - I_{\min}}{L}, \tag{16}$$

where $A(I)$ is the image mean and L the dynamic range (typically 255). BIE penalizes uniform and noisy images while rewarding balanced contrast with perceptually meaningful variation.

Figure 3 shows a thermal image and two distorted versions, all sharing identical histograms. Table 2 lists entropy-based metric values for these images. While global metrics like E and SD remain unchanged, BIE successfully detects the distortions. In contrast, EME and AME often increase in noisy cases, revealing their higher sensitivity to noise and reduced reliability.

Section 3.4 evaluates the BIE metric across several thermal datasets. Computer simulation results show that BIE yields consistent rankings for enhancement methods and correlates better with visual quality than AME or Shannon entropy. The section also introduces optimization frameworks using Genetic Algorithms (GA) and the Bat Algorithm (BA), with BIE as the objective function:

$$\max_{p_1, p_2, \ldots, p_n} BIE(F(I_s, p_1, ..., p_n)), \tag{17}$$

where F denotes the image enhancement function applied to the source image I_s, and $p_1, ..., p_n$ are the tunable parameters of the enhancement method. The goal is to find the parameter set that maximizes the Block-wise Image Entropy (BIE), yielding optimal visual quality. For example, Figure 4 shows the optimization of the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm, which enhances image contrast by applying localized histogram equalization while limiting noise amplification. The parameters tuned include clip limit (CL) in the range [1, 60] and grid size (GS) in [4, 40]. In the first case, both default settings and Shannon entropy–based optimization result in over-enhanced, noisy images. In contrast, BIE selects optimal parameters (CL = 6, GS = 4), producing visually superior results.

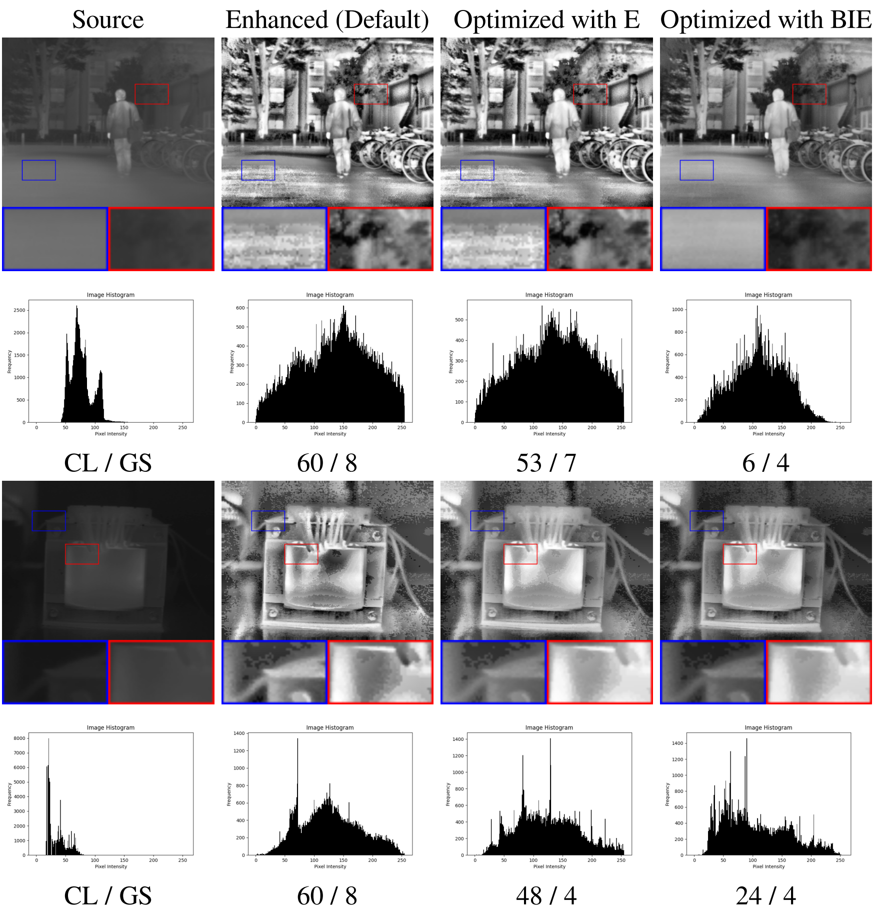

Figure 4: Results of the optimization of CLAHE algorithm (clip limit (CL) and grid size (GS) parameters) using E and BIE metrics.

Finally, the chapter introduces a BIE-weighted image fusion model, which serves as an effective application of the thermal image quality measure:

$$I_f = \frac{\sum_{i=1}^{N} m_i I_i}{\sum_{i=1}^{N} m_i}, \tag{18}$$

where I_i are enhanced images and m_i their BIE scores.

Section 3.5 concludes the chapter by summarizing the key findings: the BIE metric addresses limitations in traditional entropy and block-wise measures, offering a perceptually consistent and noise-robust quality criterion for thermal images. Its integration into parameter tuning and image fusion pipelines demonstrates utility across multiple image enhancement frameworks and datasets. BIE is shown to facilitate reliable thermal image assessment and optimization, advancing uncertainty quantification and visual clarity in critical infrared imaging tasks.

In Chapter 4, a novel thermal-specific augmentation strategy is introduced to address data scarcity challenges in fault classification tasks, particularly for photovoltaic (PV) modules. The chapter begins by discussing the limitations of conventional augmentation techniques when applied to thermal data, highlighting how unique infrared characteristics demand tailored strategies. It then presents the use of Block-wise Image Entropy (BIE), a no-reference image quality assessment metric, as the foundation for a metric-driven augmentation pipeline.

Section 4.1 provides background on thermal image classification and outlines the motivation for quality metric-based augmentation. It details the shortcomings of traditional augmentation methods, such as flips, brightness adjustments, and histogram equalization, when applied to thermal imagery, and reviews recent works that incorporate deep networks or GANs for thermal data expansion.

Section 4.2 introduces the proposed method in detail. It begins by defining the BIE metric, which incorporates both global and local image characteristics, making it well-suited for evaluating thermal image quality without the need for a reference image. This section explains how each thermal image is enhanced using parametric contrast stretching, with stretching limits optimized to maximize the BIE score. For each original image, the enhancement parameters that yield the top two BIE values are used to create two new augmented samples. These enhanced images, along with the original, are then used to expand the dataset. The process ensures that augmented samples are not arbitrary but are perceptually and structurally meaningful according to the thermal quality metric.

Section 4.3 presents the experimental setup, including datasets, training configurations, and the neural network architectures employed for evaluation, ranging from AlexNet to Swin Transformer. It compares performance metrics across several augmentation schemes, such as geometric, brightness-based, and BIE-based strategies, reporting improvements in accuracy, precision, recall, and specificity. The section notes particularly strong gains on lightweight networks like MobileNetV3, where contrast-aware augmentation significantly boosts generalization.

Section 4.4 concludes the chapter by reaffirming the practicality and effectiveness of the proposed technique. It outlines future directions, including the development of thermal-specific deep architectures and the refinement of augmentation policies for broader thermal imaging applications.

In Chapter 5, a lightweight neural network architecture called SlantNet is proposed for efficient and accurate classification of faults in thermal images of photovoltaic (PV) systems. The chapter introduces the need for computationally efficient models in large-scale solar installations and presents SlantNet as a solution combining Slant Convolutional layers with thermal-specific data augmentation to enable real-time inference and robust fault identification.

Section 5.1 introduces the motivation and challenges associated with PV system fault detection using thermal imagery. It highlights the limitations of manual inspection and traditional electrical testing, emphasizing the need for automated, scalable approaches. The section also outlines the opportunity to enhance classification models with directional and spectral feature sensitivity.

Section 5.2 provides technical background on image transforms, particularly the Slant Transform (SLT), and its relevance to thermal imaging. It explains how SLT is well-suited for encoding linear brightness gradients and piecewise structures, making it ideal for capturing fault-relevant patterns in low-resolution thermal data. The section reviews related work on harmonic convolutions and lightweight CNN models.

Section 5.3 presents the proposed method in depth. It introduces Slant Convolution (SC) as a replacement for traditional learnable filters. These SC layers use fixed SLT basis functions, enhanced by trainable weights (α, γ) that modulate the frequency response using a logarithmic transformation. The section describes how the SC layer improves interpretability and efficiency by leveraging structured directional features. The architecture of SlantNet is then detailed: it comprises two SC blocks followed by max-pooling, fully connected layers, and dropout regularization. Input images are processed at a resolution of 40×40, making the network suitable for mobile and embedded devices. Furthermore, the augmentation pipeline includes geometric flips, contrast enhancement based on the BIE metric, and optimal decolorization guided by the TIA metric, targeting class imbalance and thermal feature preservation. This combination yields a highly optimized training set with improved visual discriminability of rare fault types.

Figure 5 compares standard and Slant Convolution pipelines. While standard convolution learns spatial filters directly from data, Slant Convolution first projects the input onto a fixed harmonic basis and then modulates it using trainable logarithmic pa-

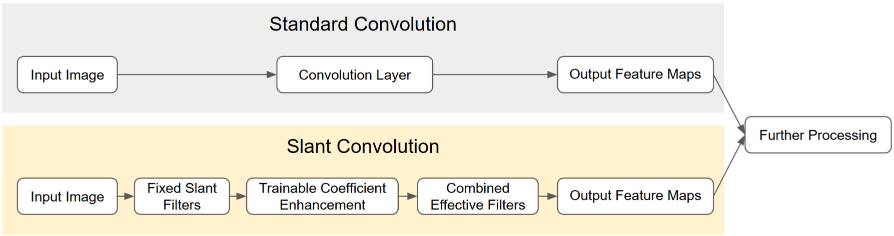

Figure 5: Comparison of Standard Convolution and Slant Convolution. Standard convolution learns arbitrary filters directly from data, while Slant Convolution first decomposes the input using a fixed harmonic basis and then applies trainable logarithmic enhancement to generate effective filters that better capture directional intensity variations.

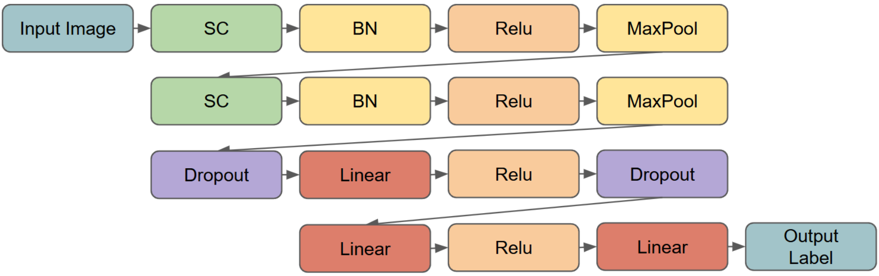

Figure 6: Overall architecture of the proposed SlantNet model incorporating the Slant Convolution (SC) layers.

rameters. This structured process enhances the extraction of directional and frequency-dependent features.

Figure 6 illustrates the overall structure of the network, comprising two convolutional blocks, max-pooling layers, and a fully connected classifier. Below, we describe the architecture in detail, along with the parameters and output dimensions for each layer.

Section 5.4 reports experimental results and comparisons. The section benchmarks SlantNet against AlexNet, ResNet50, MobileNetV3, EfficientNet, ShuffleNetV2, and Swin Transformer on binary and 12-class PV fault classification tasks. Evaluation metrics include accuracy, precision, recall, and specificity. SlantNet achieves the highest binary classification accuracy (95.1%) and competitive multiclass accuracy (82.75%), outperforming all evaluated models in classification performance. Full metric results are presented in Tables 3 and 4. In terms of efficiency, SlantNet also delivers the high-

Table 3: Classification Performance on the Validation and Test Sets for binary classification

Model	Test				Validation			
	Acc	Pr	Rec	Sp	Acc	Pr	Rec	Sp
AlexNet	92.45	93.21	91.63	93.27	92.80	94.31	91.11	94.49
ResNet50	92.65	92.98	92.33	92.97	92.05	92.18	91.91	92.19
SqueezeNet	89.60	92.25	86.55	92.67	88.75	92.08	84.82	92.69
ShuffleNetV2	92.95	93.02	92.93	92.97	92.20	93.07	91.21	93.19
MobileNetV3	93.30	93.07	93.63	92.97	92.95	93.26	92.61	93.29
EfficientNet	93.50	94.87	92.03	94.98	94.05	95.37	92.61	95.50
ViT	88.05	89.80	85.96	90.16	88.40	90.69	85.61	91.19
Swin	91.35	92.27	90.34	92.37	91.75	93.36	89.91	93.59
Proposed	**95.10**	**95.48**	**94.72**	**95.48**	**94.35**	**95.40**	**93.21**	**95.50**

Table 4: Classification Performance on the Validation and Test Sets for 12-class classification

Model	Test				Validation			
	Acc	Pr	Rec	Sp	Acc	Pr	Rec	Sp
AlexNet	77.50	61.41	58.50	97.61	77.95	65.40	60.16	97.59
ResNet50	78.75	66.45	62.56	97.68	78.35	67.32	60.94	97.62
SqueezeNet	76.70	62.46	57.41	97.46	77.85	67.20	59.16	97.49
ShuffleNetV2	79.30	66.43	62.59	97.78	80.65	72.32	64.00	97.82
MobileNetV3	82.10	68.11	67.92	98.11	81.60	71.32	64.93	98.05
EfficientNet	82.20	69.37	**71.05**	**98.19**	82.55	72.35	**69.51**	98.18
ViT	74.70	60.60	54.76	97.17	75.65	65.26	57.57	97.16
Swin	80.45	65.93	63.19	97.98	81.55	71.61	66.77	98.02
Proposed	**82.75**	**69.52**	66.83	98.15	**84.30**	**74.06**	66.67	**98.28**

est throughput at approximately 55,000 images per second, making it well-suited for real-time applications.

Section 5.5 concludes the chapter by summarizing the contributions of SlantNet in advancing thermal image classification. It reiterates the benefits of integrating spectral transforms with deep learning and highlights the success of metric-based augmentation. Future directions include deployment in drone or IoT systems using TinyML, adaptation to other domains such as wind turbines and medical imaging, and exploration of other fast orthogonal transforms for further efficiency gains.

Chapter 6 concludes the dissertation by synthesizing the key innovations developed across four interrelated studies into a unified thermal image analysis framework tailored for photovoltaic (PV) fault detection. It reflects on how the proposed no-reference quality metrics, entropy-based enhancement, quality-guided augmentation, and the Slant-

Net architecture collectively address the challenges of low-resolution, noisy, and imbalanced thermal datasets. These contributions advance both the theoretical foundations and practical implementations of thermal imaging in renewable energy diagnostics. The chapter also outlines the broader impact of this work—demonstrating its scalability, generalizability, and applicability to edge deployment and multi-modal infrastructure monitoring—while highlighting promising future directions in autonomous inspection, cross-modal learning, and scalable AI systems for thermal diagnostics.

Main Results of the Research

This dissertation introduces a unified framework for thermal image analysis and classification, with particular focus on solar photovoltaic (PV) fault detection. The research is grounded in four key contributions:

- Proposed two no-reference image quality metrics, TIA and WTIA, that assess perceptual fidelity in color-to-grayscale conversion by combining chrominance retention and edge-aware contrast, improving grayscale preprocessing for thermal data [1].
- Developed a new entropy-based quality metric tailored for thermal images, which integrates block-wise entropy, standard deviation, and average deviation percentage (ADP) to guide contrast enhancement and quantify uncertainty in low-resolution and noisy thermal imagery [2].
- Introduced a quality-driven augmentation technique that selects contrast-enhanced samples based on the BIE metric, enabling the generation of diagnostically meaningful samples and significantly improving classification performance under class imbalance [3].
- Designed *SlantNet*, a lightweight CNN architecture that incorporates Slant Transform-based harmonic convolutions, enabling efficient directional feature extraction and achieving state-of-the-art accuracy and throughput for PV fault classification with low computational cost [4].

These contributions form a coherent and scalable pipeline for robust, interpretable, and computationally efficient thermal image analysis. The proposed methods have broad applicability to real-time fault detection in solar infrastructure and can be extended to other domains such as wind turbine monitoring, transformer diagnostics, and industrial inspection. Future work will focus on integrating this framework into multi-modal, drone-based inspection systems, exploring label-efficient training through self-supervision and federated learning, and releasing an open-source toolkit to support widespread adoption.

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ence Committee of the Republic of Armenia, under project No. 25FAST-1B001.

List of Published Works

[1] H. Ayunts and S. Agaian, “No-reference quality metrics for image decolorization”, *IEEE Transactions on Consumer Electronics*, vol. 69, no. 4, pp. 1177–1185, 2023.

[2] H. Ayunts, A. Grigoryan, and S. Agaian, “Novel entropy for enhanced thermal imaging and uncertainty quantification”, *Entropy*, vol. 26, no. 5, p. 374, 2024.

[3] H. Y. Ayunts, “Enhancing thermal image classification with novel quality metric-based augmentation techniques”, *Mathematical Problems of Computer Science*, vol. 62, pp. 112–125, 2024.

[4] H. Ayunts, S. Agaian, and A. Grigoryan, “Slantnet: A lightweight neural network for thermal fault classification in solar pv systems”, *Electronics*, vol. 14, no. 7, p. 1388, 2025.

ՊԱՏԿԵՐԻ ՄՇԱԿՄԱՆ ՄԵԹՈԴՆԵՐԻ ՕՊՏԻՄԱԼԱՑՈՒՄ և ԿԻՐԱՌՈՒԹՅՈՒՆՆԵՐ

Աբստրակտ

Արևային ֆոտովոլտային համակարգերի զանգվածային ներդրումը աճեցրել է ավտոմատ, ցածր ծախսով մոնիտորինգի մեթոդների պահանջը՝ ուղղված միկրոճաքերի, միացումների կոռոզիայի և ջերմային սխալների հայտնաբերմանը, որոնք նվազեցնում են էներգիայի արդյունաբերումը: Ինֆրակարմիր ջերմային պատկերների մշակումը կարող է բացահայտել այդ թերությունները, սակայն դրանց ցածր կոնտրաստը, սահմանափակ չափերը և աղմուկը խանգարում են դասական համակարգչային տեսողության ալգորիթմներին:

Ինֆրակարմիր պատկերների անոմալիաների հայտնաբերման համար այս դիսերտացիայում մշակվել է տվյալաարդյունավետ, որակի գնահատման վրա հիմնած պրոցես: Աշխատանքային շղթան ներառում է բարելավում, տվյալների ընդլայնում և թեթև նեյրոնային ցանցեր՝ հաղթահարելով տեսանելի սպեկտրի մեթոդների սահմանափակումները:

Նախ առաջարկվում են TIA և WTIA որակի չափիչներ, որոնք քանակապես գնահատում են պատկերի որակը գունաթափման ընթացքում [1]: Այս չափիչները գերազանցում են CCPR և E-score մեթոդներին՝ ապահովելով աղավաղումներից զերծ գունաթափում: Ջերմային պատկերների համար ներկայացվում է բլոկային ինֆորմացիոն էնտրոպիայի (BIE) նոր չափիչ, որը միավորում է գլոբալ վիճակագրությունն ու տեղային կառուցվածքը: BIE-ն ուղղորդում է գենետիկ և չղջիկի ալգորիթմներով հենվող օպտիմալացումներ՝ բարելավելով կոնտրաստը և վերահսկելով աղմուկը [2]: BIE-ն նաև օգտագործվում է տվյալների ընդլայնման համար, որը ստեղծում է իրատեսական սինթետիկ նմուշներ՝ բարձրացնելով դասակարգման ճշգրտությունը՝ փոքր տվյալների պայմաններում [3]: Ջերմային պատկերների դասակարգման համար առաջարկվում է SlantNet ցանցը, որը ներառում է սլենտ կոնվոլյուցիաներ (Slant Convolution): 40 × 40 ջերմային պատկերների վրա այն նվազեցնում է հաշվարկային բարդությունը ~60%-ով՝ գերազանցելով CNN-ների ճշգրտությունը [4]:

Այս ներդրումները միասին ձևավորում են արագ, հուսալի և լայն կիրառելի ջերմային պատկերի վերլուծություն, կիրառելի նաև հողմաղացների, տրանսֆորմատորների և բժշկական պատկերների համար՝ աջակցելով խոշորածավալ, էներգիա-խնայող մոնիտորինգին:

Աշխատանքի նպատակը և դիտարկված խնդիրները

Աշխատանքի նպատակը թերությունների ճշգրիտ հայտնաբերման համար արդյունավետ խողովակաշար մշակելն է, որն օպտիմալացված է արևային վահանակների ստուգման և ցածր հզորությամբ սարքերում տեղակայման համար:

Խնդիրներն են՝ նախագծել որակի չափիչներ (TIA/WTIA), մշակել աղավաղումների նկատմամբ կայուն, էնտրոպիայի վրա հիմնված ջերմային պատկերների բարելավում, ստեղծել տվյալների հավաքածուի աուգմենտացիայի մեթոդ, մշակել SlantNet ցանցը՝ արդյունավետ դասակարգման համար, և ամբողջ շղթան ինտեգրել միավորված համակարգում՝ փորձարկելով բազմաբնույթ ջերմային տվյալների վրա:

Ստացված արդյունքների կիրառական նշանակություն

Աշխատանքում ներկայացված գործիքները ապահովում են պատկերների արդյունավետ գնահատում և դասականգում՝ իրական ժամանակում, հարմարեցված դրոնների, ներկառուցված սարքերի և եզրային համակարգերի վրա կիրառման համար: Շղթան՝ ներառյալ առանց հղման որակի չափիչները, հարմարվող բարելավումը և SlantNet մոդելը, նվազեցնում է դասակարգման ժամանակը՝ բարձրացնելով արևային վահանակների արդյունավետությունը: Մեթոդները նաև կիրառելի են տեսահսկման, արդյունաբերական և անվտանգության մոնիտորինգի ոլորտներում.

Աշխատանքի ծավալը և կառուցվածքը

Աշխատանքը ընդգրկում է 115 էջ՝ ներառյալ ներածություն, չորս գլուխ և եզրակացություն: Այն պարունակում է 132 գրականության աղբյուր:

Աշխատանքի հիմնական արդյունքները

Աշխատանքում ներկայացված է ջերմային պատկերի վերլուծության և դասակարգման միավորված շրջանակ, կենտրոնացած՝ արևային ֆոտովոլտային դեֆեկտների հայտնաբերման վրա: Հիմնական արդյունքները հետևյալն են.

- Առաջարկվել են TIA և WTIA ոչ-հղման որակի չափիչներ՝ գունաթափման ընթացքում կառուցվածքային և գունային տեղեկատվության պահպանումը գնահատելու համար [1]:
- Մշակվել է ջերմային պատկերների համար հարմարեցված նոր էնտրոպիայով չափիչ, որը ներառում է բլոկային էնտրոպիա, ստանդարտ շեղում և միջին շեղման տոկոս՝ հակադրության բարելավման և անորոշության քանակականացման համար [2]:
- Ներկայացվել է տվյալների ընդլայնման մեթոդ, որը ընտրում է բարձր որակի նմուշներ BIE չափիչի միջոցով՝ ավելացնելով դասակարգման արդյունավետությունը դասերի անհավասարակշռության պայմաններում [3]:
- Ներդրվել է *SlantNet*՝ թեթև նեյրոնային ցանց, որը ներառում է սլենտ կոնվոլյուցիաներ՝ ուղղորդված առանձնահատկությունների արդյունավետ հանման համար՝ ապահովելով բարձր ճշգրտություն և արագություն [4]:

ОПТИМИЗАЦИЯ МЕТОДОВ ОБРАБОТКИ ИЗОБРАЖЕНИЙ И ИХ ПРИМЕНЕНИЯ

Аннотация

Масштабное внедрение солнечных фотоэлектрических (ФЭ) систем усилило потребность в автоматических и недорогих методах инспекции для выявления дефектов, таких как микротрещины, коррозия соединений и термические аномалии, снижающие выработку энергии. Инфракрасная термография способна выявлять такие неисправности, однако её низкий контраст, ограниченное разрешение и высокая чувствительность к шуму затрудняют использование традиционных методов компьютерного зрения.

В данной диссертации разработан эффективный по данным и качественно-ориентированный рабочий процесс, адаптированный к инфракрасным изображениям для диагностики неисправностей в ФЭ модулях. Предлагаемый конвейер объединяет улучшение качества, расширение данных и лёгкую классификацию, преодолевая ограничения методов, разработанных для видимого спектра.

Представлены два безэталонных показателя качества изображений — TIA и WTIA, которые оценивают сохранение контраста при преобразовании в оттенки серого без необходимости использования эталонных изображений [1]. Эти метрики превосходят классические CCPR и E-score, позволяя проводить преобразование без искажений. Для тепловизионных изображений предложена новая метрика энтропии по блокам (BIE), объединяющая глобальные статистические и локальные структурные признаки. BIE также служит целевой функцией в алгоритмах оптимизации на основе генетических и алгоритма летучих мышей, повышая контраст и подавляя шум [2]. Кроме того, BIE управляет стратегией генерации синтетических данных с оптимизированным контрастом, значительно повышая точность классификации в условиях ограниченных данных [3]. Для работы на устройствах с ограниченными ресурсами разработана модель SlantNet — свёрточная нейросеть с фиксированными наклонными гармоническими ядрами. На изображениях размером 40×40 она снижает количество операций с плавающей точкой примерно на 60% при сохранении точности, сопоставимой с тяжёлыми моделями CNN и Transformer [4].

В совокупности данные разработки формируют комплексное решение для термографической диагностики, отличающееся скоростью, надёжностью и применимостью в других инфракрасных задачах — от диагностики ветроустановок до мониторинга трансформаторов и медицинской визуализации.

Основная цель работы и задачи

Целью является создание легковесного и завершённого конвейера для точного обнаружения тепловых дефектов, оптимизированного для обследования солнечных панелей и пригодного для размещения на маломощных устройствах.

Ключевые задачи включают: разработку безэталонных метрик качества (TIA/WTIA); создание метода контрастного улучшения на основе энтропии; генерацию синтетических данных для балансировки редких классов; проектирование эффективной модели SlantNet; интеграцию всех компонентов в единый открытый программный комплекс, протестированный на различных тепловизионных наборах данных.

Практическая значимость полученных результатов

Предложенные в работе инструменты обеспечивают эффективную и доступную тепловизионную инспекцию в реальном времени, адаптированную для использования на дронах, встроенных устройствах и пограничных системах. Интеграция безэталонных метрик качества, адаптивного улучшения и лёгкой модели SlantNet позволяет сократить время проверки и простой оборудования, повышая эффективность фотоэлектрических панелей. Разработанные методы также применимы в видеонаблюдении, промышленной диагностике и системах безопасности.

Объём и структура работы

Диссертация содержит 115 страниц и включает введение, четыре главы и заключение. В работе приведены 132 библиографических источника.

Основные результаты работы

В работе представлен единый подход к обработке и классификации тепловизионных изображений с акцентом на диагностику солнечных ФЭ модулей. Основные научные результаты включают:

- Разработка двух безэталонных метрик качества изображений (TIA и WTIA), оценивающих сохранение хроматических и структурных характеристик при преобразовании изображения в оттенки серого [1].
- Введение новой энтропийной метрики для тепловизионных изображений, объединяющей блочную энтропию, стандартное отклонение и показатель средней девиации (ADP) для оценки качества и улучшения контраста [2].
- Предложен подход к генерации синтетических данных на основе метрики BIE, позволяющий создавать информативные образцы и повышать точность классификации при классовом дисбалансе [3].
- Разработана модель SlantNet — компактная CNN-архитектура с наклонными гармоническими свёртками, обеспечивающая эффективное извлечение направленных признаков и высокую точность при низкой вычислительной нагрузке [4].