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# Enhancing Target Detection: Minimum Resolvable Temperature Difference (MRTD) Optimization in Military Thermal Imagers

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**Abstract: Minimum Resolvable Temperature Difference (MRTD) remains a key indicator of thermal imaging system performance, reflecting the ability to distinguish subtle temperature variations at defined spatial frequencies. As applications expand into high-demand areas such as autonomous surveillance, military missions, and space exploration, achieving lower MRTD values becomes increasingly critical. Recent advancements highlight the transformative role of quantum detectors, like HgCdTe and Quantum Well Infrared Photodetectors (QWIPs), which offer improved sensitivity, reduced noise, and broader spectral response, significantly lowering MRTD thresholds. These technologies enhance thermal image resolution and clarity under challenging operational conditions. Concurrently, artificial intelligence (AI) is reshaping MRTD assessment by enabling real-time optimisation of imaging parameters. AI-driven algorithms adapt to environmental variables, scene complexity, and target features, facilitating automatic performance tuning and enhanced contrast. Machine learning techniques further support noise reduction and detail enhancement, pushing MRTD performance boundaries. Complementing these are adaptive resolution strategies that enable thermal systems to dynamically adjust spatial and thermal accuracy in response to operational demands. Additionally, innovations in sensor miniaturisation are fuelling the development of lightweight, portable thermal imagers for use in wearable and unmanned systems. These integrated technologies are defining a new era of high-performance, intelligent thermal imaging with unprecedented MRTD capabilities.**

***Keywords:*** *MRTD, Thermal Clutter, Scene-Dependant MRTD Algorithm, AI-Assisted TI Calibration, Real-Time Environmental Compensation, Adaptive IR Imaging System*

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## I. INTRODUCTION

Minimum Resolvable Temperature Difference (MRTD) is a foundational metric used to assess the sensitivity and resolving power of thermal imaging systems[1,2,3]. It denotes the smallest temperature differential that a system can distinguish at a specified spatial frequency, thereby linking both resolution and thermal sensitivity in a single performance indicator. Traditionally, MRTD has been measured through observer-based methods under controlled laboratory environments, where standardized targets and human evaluation are employed to determine system. While these conventional approaches provide a baseline for sensor performance, they fall short when extrapolated to the complexity of real-world conditions. As thermal imaging finds broader applications in defence, aerospace, autonomous navigation, industrial inspections, and medical diagnostics, the limitations of static MRTD measurements are becoming increasingly apparent. Environmental variables such as atmospheric attenuation, humidity, fog, and thermal clutter substantially influence system performance in the field, making it difficult to rely solely on lab-derived MRTD values. These inconsistencies highlight the urgent need for a dynamic, adaptive framework that accounts for environmental variabilities and system behaviour in real-time. The future trajectory of MRTD research is thus shifting toward intelligent systems capable of automated assessment, environmental compensation, and real-time optimization. Innovations such as AI-assisted image interpretation, physics-informed simulation models, and embedded environmental sensing are enabling next-generation thermal imagers to self-calibrate and maintain consistent performance across a range of conditions.

Additionally, scene-dependent algorithms and real-time environmental data fusion are providing new methods to quantify and minimize MRTD degradation during actual operations. This report delves into these emerging developments, focusing on how environmental conditions affect MRTD performance and what strategies, both

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computational and hardware-based, are being developed to ensure stable, reliable imaging capabilities under diverse and unpredictable scenarios. (as shown in Fig.1).

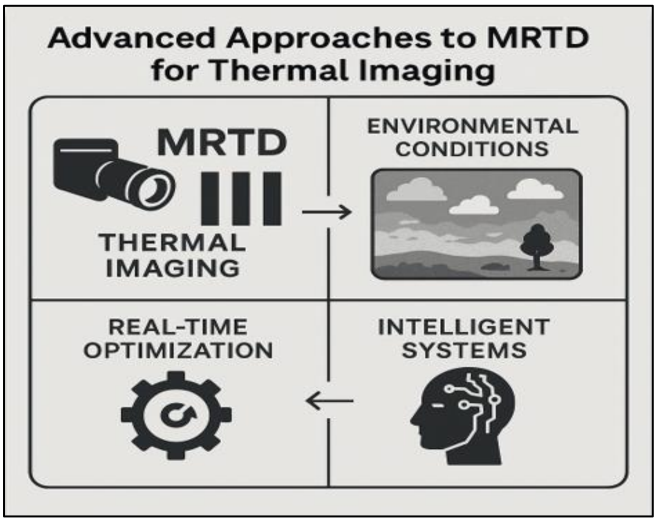


Fig 1 Schematic of Modern MRTD Interpretation Framework

## II. THE EVOLUTION OF MRTD: FROM OBSERVER MODELS TO INTELLIGENT SYSTEMS

Initial MRTD models were grounded in empirical testing using human observers and standardized bar targets (as shown in Fig.2). However, these methods are plagued by subjectivity and repeatability issues. Recent efforts have shifted toward observer-independent, AI-driven metrics that simulate human perception with high fidelity, enabling automated performance monitoring. The movement toward synthetic vision and deep-learning-enabled observer models offers a pathway for real-time MRTD estimation without human input. These tools can assess complex scenes adaptively, incorporating contextual awareness, which is not possible with conventional MRTD frameworks.


Fig 2 Target for MRTD Test.

Modern thermal imaging systems increasingly rely on real-time MRTD evaluation and embedded diagnostics, crucial for defence, aerospace, and autonomous platforms. Traditional offline MRTD testing lacks adaptability in dynamic environments. Contemporary methods use intelligent algorithms and machine learning to estimate MRTD from live video, eliminating artificial targets. These algorithms run on embedded hardware like FPGAs and GPUs, enabling low-latency processing. Integrated diagnostics monitor sensor health and environmental conditions, facilitating real-time adjustments and predictive maintenance. This approach improves reliability, operational readiness, and system longevity by enabling continuous performance tracking and proactive servicing in mission-critical applications.

## III. ADAPTIVE MRTD UNDER VARYING ENVIRONMENTAL CONDITIONS

One of the biggest future challenges lies in maintaining low MRTD under unpredictable and dynamic environmental conditions. Atmospheric turbulence, humidity, and cluttered backgrounds degrade performance significantly. Emerging trends focus on:

- Environmental compensation algorithms
- Scene-based adaptive contrast enhancement
- Real-time correction filters integrated into the image processing pipeline

Research is also exploring multispectral fusion systems where visible and IR data are combined to minimize MRTD degradation Minimum Resolvable Temperature Difference (MRTD), while fundamentally a property of a thermal imaging system, is significantly influenced by environmental factors that distort, attenuate, or obscure thermal signatures. As thermal imagers are increasingly deployed in diverse real-world scenarios—including battlefield surveillance, search and rescue operations, industrial inspections, and space missions—the ability of these systems to maintain consistent MRTD under fluctuating environmental conditions has become a critical research focus. Environmental conditions introduce various sources of error and uncertainty that degrade thermal image quality. Key among these is atmospheric attenuation, humidity, wind, ambient temperature, solar loading, and background clutter. For instance, atmospheric gases such as water vapor and carbon dioxide absorb and scatter infrared radiation in specific spectral bands, resulting in contrast loss and reduced thermal sensitivity. High humidity can cause water droplets in the air to scatter thermal energy, creating noise in the image and increasing the effective MRTD. Moreover, in outdoor environments, solar heating and reflections from terrain and objects introduce additional thermal gradients that may mask or distort target features. These dynamic and spatially varying interferences cause thermal imagers to suffer from elevated MRTD values, especially when attempting to resolve low-contrast targets against complex backgrounds. To address these challenges, adaptive MRTD techniques are being developed (as shown in Fig.3). These include both hardware-based and software-driven solutions. On the hardware side, sensors with broader dynamic range and higher thermal sensitivity (e.g., using vanadium oxide or Type-II superlattice detectors) help in distinguishing targets from noisy

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backgrounds. Spectral filtering is also used to isolate useful infrared bands less affected by atmospheric absorption. Software-driven adaptive compensation techniques are where much of the innovation is currently focused. Scene-based non-uniformity correction (SBNUC) is one such technique that continuously adjusts detector response based on real-time scene analysis, correcting for fixed pattern noise and dynamic drift.

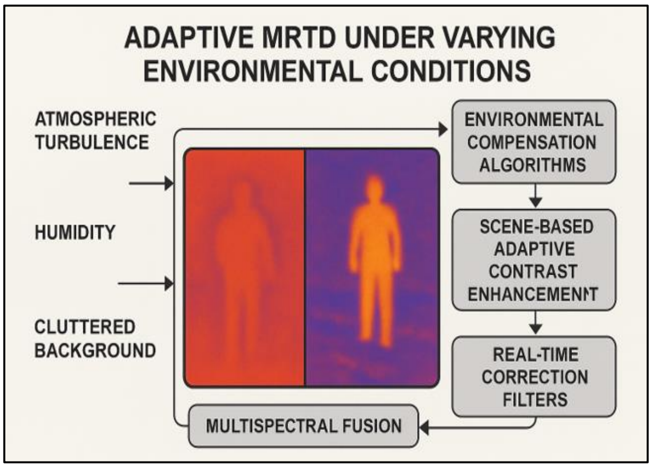


Fig 3 Schematic of Adaptive MRTD Under Varying Environmental Conditions

Additionally, contrast enhancement algorithms dynamically adjust brightness and contrast parameters to emphasize subtle thermal differences in cluttered environments. More advanced systems incorporate machine learning models trained to recognize and classify environmental interference patterns. Recent research also focuses on fusing data from multiple sensors, such as combining visible light, near-infrared, and long-wave infrared (LWIR) imaging, to mitigate the effects of environmental degradation. Another promising direction is the development of physics-informed MRTD models that integrate real-time environmental sensing. By embedding temperature, humidity, and atmospheric pressure sensors within the imaging system, it becomes possible to dynamically correct for environmental factors using radiative transfer models like MODTRAN. Adaptive MRTD under varying environmental conditions is a multifaceted challenge that requires the convergence of advanced sensor technologies, real-time signal processing, and AI-based interpretation. The goal is to ensure that thermal imagers can maintain optimal performance regardless of operational context.

## IV. REAL-TIME MRTD EVALUATION AND EMBEDDED DIAGNOSTICS

The integration of embedded diagnostics within thermal imagers is gaining attention. These modules can perform on-the-fly MRTD assessment using AI classifiers trained on large thermal datasets. In field-deployed scenarios like UAVs or missile seekers, these self-diagnostic tools offer autonomous performance validation, reducing dependency on external calibration. Microcontroller- and FPGA-based solutions are being developed to perform MRTD evaluations directly on the imaging hardware, improving responsiveness and reliability. In modern thermal imaging systems, real-time performance monitoring is essential, especially for defence, aerospace, and autonomous applications. Traditional MRTD evaluation methods, relying on offline test targets, are inadequate in dynamic or remote environments. The integration of real-time MRTD assessment with embedded diagnostics has enhanced system reliability and autonomy. These systems use adaptive algorithms to estimate MRTD from live video feeds, removing the need for artificial targets. Key metrics like contrast, edge sharpness, and thermal gradients are analysed on a per-frame basis using machine learning or statistical models. These algorithms operate on embedded platforms such as FPGAs, GPUs, or microcontrollers, enabling fast, efficient diagnostics. This is vital for mobile platforms, ensuring real-time feedback without external computation. Furthermore, embedded MRTD diagnostics often integrate with other sensor modules to contextualize system performance. For instance, thermal sensors embedded with temperature, humidity, and vibration detectors can infer whether environmental factors are causing performance degradation. By fusing this data with image-based MRTD estimations, the system can apply real-time corrections, adjust processing algorithms, or alert operators to specific anomalies.

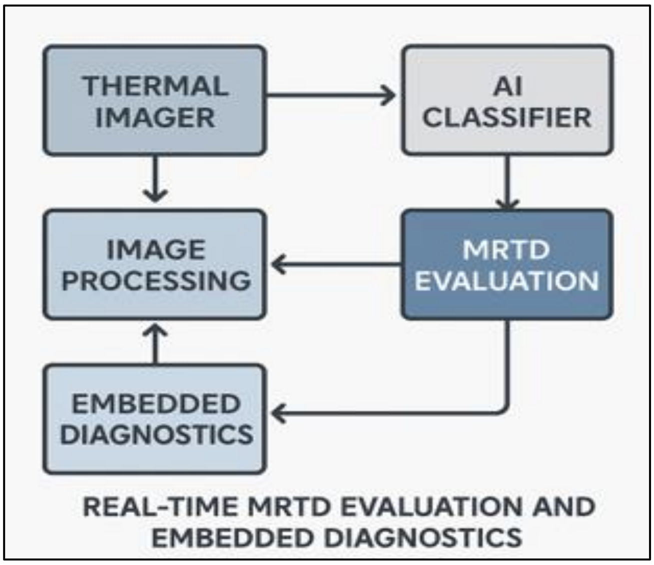


Fig 4 Block Diagram for Real-Time MRTD Evaluation

Advanced systems even include feedback loops that optimize system parameters such as integration time, gain control, or digital filtering based on MRTD outputs. If the MRTD begins to rise due to sensor noise or thermal drift, the system may automatically enhance image stabilization, perform flat-field correction, or adjust lens focus. By continuously tracking MRTD trends over time, embedded systems can forecast performance degradation and recommend servicing or component replacement before failure occurs. This reduces downtime, enhances reliability, and extends the operational lifespan of the system—benefits that are especially valuable in military and aerospace domains. A real-time MRTD evaluation and embedded diagnostics represent a leap forward (as shown in Fig.4) in thermal imaging system design. These technologies enable

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thermal imagers to become self-aware, self-adjusting, and self-monitoring—characteristics that are essential in modern, data-driven operational environments.

## V. MINIATURIZATION AND MRTD SCALING LAWS IN MICRO/NANO-IR SENSORS

The trend toward smaller, lightweight imaging platforms demands that MRTD remain optimized even in miniaturized formats. Research in microbolometer arrays, photonic IR sensors, and MEMS-integrated IR systems shows promise. However, challenges such as thermal cross-talk, reduced fill-factor, and quantum noise continue to affect MRTD at micro-scales. New scaling laws are being proposed to understand the interplay between sensor geometry and thermal sensitivity, offering a pathway to predict MRTD for nanoscale devices. As thermal imaging technology advances toward portability, integration into wearables, unmanned platforms, and miniaturized surveillance systems, the push toward smaller and lighter infrared (IR) sensors have intensified. This trend, driven by both military and commercial demands, introduces new challenges in maintaining imaging performance, especially in terms of the Minimum Resolvable Temperature Difference (MRTD). The miniaturization of thermal imagers must contend with fundamental scaling laws that affect thermal sensitivity, resolution, and signal-to-noise characteristics. MRTD, in its classical definition, is influenced by the interplay of optical resolution, detector sensitivity, and noise performance. When transitioning from macro-scale systems to micro- and nano-scale devices, several factors fundamentally change. Chief among them are reductions in aperture size, pixel pitch, and thermal capacity—all of which impact the system's ability to detect and resolve small temperature differences. One major issue is the diffraction limit imposed by smaller optical elements. As lens sizes shrink, the ability of the system to focus infrared radiation sharply diminishes due to increased diffraction effects. This causes a broadening of the point spread function (PSF), leading to lower spatial resolution and increased MRTD. Moreover, the numerical aperture of miniaturized optics decreases, capturing less thermal radiation, which directly impacts detector sensitivity. Miniaturized detectors, such as those based on microbolometers or quantum well infrared photodetectors (QWIPs), face challenges related to thermal isolation and noise. As pixel sizes reduce to accommodate higher resolution on small dies, the thermal mass of individual pixels also decreases, making them more susceptible to ambient fluctuations and electronic noise. This increases the noise-equivalent temperature difference (NETD), which correlates directly with MRTD degradation. Similarly, smaller detectors have lower signal levels due to reduced photon collection, necessitating more sensitive readout electronics and advanced noise reduction algorithms. To counter these effects, researchers are exploring new materials and architectures at the micro- and nanoscale. Vanadium oxide (VOx) and amorphous silicon microbolometers have been engineered for enhanced thermal isolation and higher responsivity. Further, nanostructured materials, including plasmonic meta-surfaces and superlattices, are being developed to manipulate and enhance IR absorption at specific wavelengths. These technologies promise to reduce MRTD by improving detector efficiency despite the constraints of miniaturization. Another strategy involves computational compensation. Super-resolution imaging techniques are being used to overcome physical resolution limits, while AI-driven post-processing can reconstruct thermal images with an apparent lower MRTD by enhancing contrast and reducing noise. However, through innovative material science, novel fabrication techniques, and AI-enabled compensation algorithms, it is increasingly possible to achieve high-performance thermal imaging in miniature form factors.

## VI. QUANTUM THERMAL IMAGING AND THE THEORETICAL MRTD LIMIT

➢ *Role of Quantum Detectors in Redefining MRTD Limits*

Quantum infrared imaging, especially using photon entanglement and squeezed light states, is an emerging frontier. These techniques theoretically allow sub-shot-noise-level thermal detection, potentially lowering MRTD beyond classical physical limits. While still experimental, quantum-enhanced thermal sensors could achieve MRTD values an order of magnitude lower than state-of-the-art cryogenically cooled systems. Quantum detectors represent a cutting-edge advancement in thermal imaging technology, offering unparalleled sensitivity, spectral selectivity, and low-noise performance (as shown in Fig.5). These characteristics position them as critical enablers for pushing the boundaries of Minimum Resolvable Temperature Difference (MRTD), particularly in applications that demand ultra-precise thermal resolution under challenging conditions such as low signal environments, long-range surveillance, and deep-space exploration. Traditional thermal detectors like microbolometers rely on changes in material resistance due to absorbed infrared radiation. While effective and relatively inexpensive, their performance is constrained by thermal inertia, limited spectral sensitivity, and higher noise-equivalent temperature differences (NETD). In contrast, quantum detectors such as Mercury Cadmium Telluride (HgCdTe), Type-II Superlattices (T2SL), Quantum Well Infrared Photodetectors (QWIPs), and Quantum Dot Infrared Photodetectors (QDIPs) utilize quantum mechanical effects like interband and intersubband transitions to detect incident infrared photons directly. One of the most profound advantages of quantum detectors is their high detectivity (D*), which allows them to discern extremely small differences in thermal radiation. Since MRTD is inversely related to both signal strength and system contrast, detectors with high D* values significantly lower the MRTD threshold by maximizing the response to minute temperature differences while minimizing noise. This is especially important in applications such as early warning systems, airborne targeting pods, and thermal astronomy, where detecting faint or distant heat sources is critical. Quantum detectors also offer tunable spectral sensitivity across mid-wave infrared (MWIR) and long-wave infrared (LWIR) bands, and even into the short-wave infrared (SWIR) regime. This spectral tunability enables optimization of MRTD performance for specific operational wavelengths. Another transformative feature of quantum detectors is their high-speed operation, with response times in the nanosecond to

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microsecond range. This allows thermal imagers to operate at high frame rates, which is particularly valuable in dynamic scenarios such as missile guidance or hypersonic object tracking. Advancements in cryogenic and thermoelectric cooling have also addressed one of the primary challenges of quantum detectors—the need for low operating temperatures.

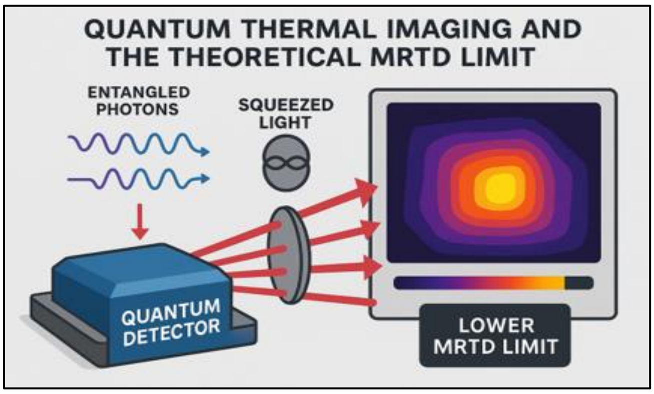

Fig 5 Quantum Detectors in Redefining MRTD Limits

In addition, quantum detector arrays are being integrated with on-chip processing to support intelligent signal conditioning and real-time MRTD evaluation. With the emergence of digital readout integrated circuits (DROICs) and system-on-chip (SoC) architectures, quantum detector-based imagers are now capable of embedded diagnostics, dynamic range adaptation, and machine learning-based MRTD prediction. Quantum detectors are redefining the theoretical and practical limits of MRTD by providing high sensitivity, spectral agility, and fast response within compact platforms.

## VII. AI AND MACHINE LEARNING FOR PREDICTIVE MRTD MODELS

Deep learning is revolutionizing thermal image processing. Predictive models can now estimate MRTD in real time, factoring in operational conditions, sensor status, and scene complexity. These models can also learn to optimize system parameters—like gain, integration time, and filter coefficients—to keep MRTD within mission-specific thresholds. Transfer learning and federated learning approaches are being considered to adapt MRTD models across different sensor platforms without needing retraining. The application of machine learning (ML) in thermal imaging has revolutionized the way we evaluate and optimize Minimum Resolvable Temperature Difference (MRTD). Historically, MRTD was determined through physical modelling or manual observation, but such methods are constrained by simplifications and human subjectivity. Machine learning introduces a paradigm shift, offering data-driven approaches that can predict, enhance, and adapt MRTD performance dynamically and with unprecedented precision. At the core of ML-based MRTD evaluation is the ability of algorithms to learn complex, nonlinear relationships between image quality, sensor characteristics, environmental conditions, and system output. One of the major advantages of ML in this domain is its capacity for real-time adaptability. Unlike traditional threshold-based systems, ML models can generalize across different scenes, noise levels, and operational contexts, making them more robust to real-world variability. In addition to prediction, ML is increasingly being used for enhancement, actively improving the MRTD of a thermal image by optimizing contrast and reducing noise. Denoising autoencoders and generative adversarial networks (GANs) have proven effective in this regard. These models learn the statistical structure of thermal noise and can reconstruct cleaner, higher-quality thermal images from noisy inputs. This effectively lowers the apparent MRTD by revealing finer thermal details that would otherwise be lost. Moreover, hybrid approaches are emerging that integrate physics-based thermal models with ML algorithms. These physics-informed neural networks (PINNs) embed the governing equations of heat transfer and radiative emission directly into the ML framework, improving generalization and interpretability. Such models not only predict MRTD more accurately but also explain why performance is changing, aiding in diagnostics and system design. Despite these advances, challenges remain. Ensuring the explainability of ML predictions, dealing with data scarcity, and achieving real-time performance on low-power embedded systems are ongoing research topics. However, with the increasing availability of thermal datasets, improved edge AI hardware, and interdisciplinary collaboration, ML is rapidly becoming indispensable in the design, evaluation, and enhancement of thermal imaging systems.

## VIII. INTEGRATION WITH DIGITAL TWIN SYSTEMS

Digital twin technology is now being applied to thermal imaging systems for predictive maintenance and performance tracking. MRTD is a core metric modelled in real-time simulations of sensor health and environmental performance. These virtual replicas can help forecast when MRTD performance will degrade and recommend reconfiguration or servicing.

➢ *MRTD vs. MNRC and Emerging Performance Metrics*

While Minimum Resolvable Temperature Difference (MRTD) has long served as the primary metric for evaluating the performance of thermal imaging systems, its limitations have prompted the emergence of complementary and, in some cases, alternative measures. Among these, the Minimum Number of Resolvable Cycles (MNRC) has gained traction as a more objective and comprehensive indicator of system capability. The evolving landscape of thermal sensing technologies—particularly in high-resolution, intelligent, and multispectral systems—necessitates a re-evaluation of how we define and measure image quality and performance. MRTD traditionally assesses the minimum temperature difference between a target and its background that an observer can detect at a given spatial frequency. This test typically involves four-bar targets and human observers, introducing variability and subjectivity into the evaluation. MRTD is influenced by optics, detector sensitivity, display characteristics, and observer interpretation, making it a system-level metric. However, as imaging systems become more autonomous and incorporate AI-driven detection and interpretation, the reliance on human perception in MRTD

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testing becomes increasingly inadequate. The MNRC metric was developed in response to these limitations. Rather than focusing on temperature contrast, MNRC evaluates how many spatial cycles (or line pairs) a thermal imaging system can resolve across a range of conditions. This metric aligns better with digital image processing and algorithmic interpretation, as it is based on signal-to-noise ratios, modulation transfer functions (MTFs), and quantitative image quality analysis. In essence, MNRC provides a frequency-based resolution metric independent of subjective thermal contrast, offering a more stable and reproducible benchmark. MNRC is particularly effective for high-resolution thermal imagers where the bottleneck is not necessarily thermal sensitivity (i.e., NETD or MRTD) but the ability to maintain spatial fidelity across fine details. This is critical for applications like facial recognition in thermal imagery, pattern recognition in security monitoring, or small object tracking in missile defence. In such use cases, the system's ability to resolve numerous fine cycles, irrespective of temperature differential, becomes more relevant than traditional MRTD. Emerging performance metrics go even further. Task-based performance metrics, such as Johnson criteria (probability of detection, recognition, and identification) and Cycle-Based Thermal Contrast Metrics, are being incorporated into system evaluation, especially in military and surveillance systems where mission-specific performance is more important than theoretical limits. These metrics consider real-world constraints like motion blur, atmospheric distortion, scene dynamics, and clutter—factors not directly addressed by MRTD or MNRC. These metrics reflect how efficiently thermal systems convert physical thermal signals into actionable information, a vital capability for edge processing in resource-constrained environments (as illustrated in Fig. 6). With the rise of multispectral and hyperspectral infrared imaging, traditional MRTD is increasingly inadequate, as spectral contrast provides more meaningful differentiation than spatial resolution alone. New metrics, such as Spectral Resolution Figure of Merit (SR-FoM) and Multiband Contrast Metrics (MCM), now complement MRTD. Intelligent thermal systems are thus evaluated through task-based metrics, MNRC, and AI-driven performance models, emphasising actionable insight over static resolution thresholds.

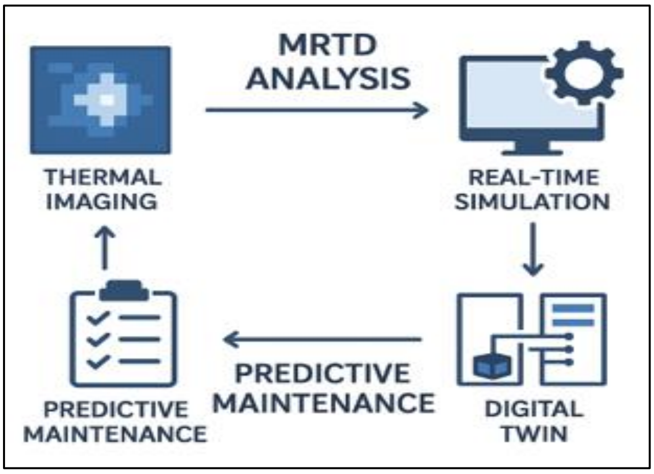


Fig 6 Integration with Digital Twin Technology & Emerging Performance Metrics

## IX. CHALLENGES IN STANDARDIZATION AND CROSS-PLATFORM EVALUATION

➢ *MRTD Standardization, AI Benchmarking & Testing Protocols*

Despite the progress, a universal framework for MRTD across various thermal platforms remains elusive. Variations in optics, processing, and detector technology complicate standardization. Future research must address:

- Platform-independent MRTD assessment tools
- Unified simulation environments
- Cross-platform MRTD correlation metrics

Efforts are underway within ISO and defence standards bodies to incorporate next-gen MRTD evaluation into future revisions of imaging standards. As thermal imaging systems evolve to include artificial intelligence (AI), machine learning (ML), and embedded smart processing, the need for rigorous Minimum Resolvable Temperature Difference (MRTD) standardization and benchmarking has become more urgent than ever. Traditional MRTD evaluation methods, developed for analog, human-interpreted systems, are increasingly insufficient in describing the performance of advanced thermal imagers that rely on digital interpretation, real-time processing, and autonomous decision-making. The integration of AI in these systems demands a rethinking of how MRTD is defined, measured, and standardized, particularly for systems operating in safety-critical environments such as defence, aerospace, search and rescue, and autonomous vehicles. Historically, MRTD testing was conducted using four-bar targets and human observers under controlled laboratory conditions. The observer's ability to resolve targets of known spatial frequency at varying temperature contrasts was recorded, resulting in an MRTD curve that characterized system performance. However, this method is both subjective and labour-intensive. It also fails to capture the nuances of digital image enhancement, machine interpretation, or multispectral fusion—all of which can influence system-level thermal discrimination in modern applications. To address this, new standardization protocols are being developed and refined by organizations such as the International Electrotechnical Commission (IEC), National Institute of Standards and Technology (NIST), and various defence research laboratories. These standards seek to replace observer-dependent tests with objective, algorithm-based assessments. For example, the IEC 62676-5 and MIL-STD-810 protocols incorporate digital image analysis techniques to determine MRTD more consistently. Automated MRTD assessment using modulation transfer functions (MTFs), edge detection, contrast-to-noise ratio (CNR), and scene-based thermal differentiation is becoming the norm. Furthermore, AI benchmarking has emerged as a complementary requirement. As many thermal imaging systems now rely on AI models for detection, classification, and tracking, evaluating the AI's contribution to MRTD performance is essential. This involves testing not just the hardware (optics, sensors) but also the software stack, including pre-processing algorithms, neural networks, and post-processing engines. Benchmarks now consider how well an AI model can detect subtle thermal anomalies, classify materials based on

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emissivity, or maintain detection under varying environmental noise. These AI-enhanced capabilities can significantly reduce the functional MRTD even if the hardware specifications remain unchanged. Testing protocols are also expanding to include scene diversity, motion blur effects, cluttered backgrounds, variable emissivity, and environmental dynamics like wind, humidity, and solar reflections. In real-world applications, thermal imagers rarely operate under ideal lab conditions. Thus, dynamic MRTD testing—using time-varying targets and scenarios—is becoming essential to reflect operational truth. Additionally, real-time diagnostics and feedback loops are being tested as part of system certification, especially in defence-grade systems where adaptive calibration and fault tolerance are mandatory. Another dimension is interoperability benchmarking. As thermal sensors are increasingly integrated into sensor fusion systems alongside LIDAR, RADAR, and visible-spectrum cameras, MRTD must be contextualized in a multisensory data framework. Standards now look at how MRTD impacts data fusion outcomes, whether AI algorithms can maintain target tracking consistency, and how thermal data integrates into broader situational awareness systems. Moreover, simulated environments and digital twins are being used to evaluate MRTD performance across hypothetical scenarios before deployment. This allows for controlled stress-testing of imaging systems against AI threats (e.g., spoofing), sensor degradation, and cyber-physical interactions that would otherwise be impractical or dangerous to test in the field. The standardization of MRTD in the era of AI-driven imaging demands a multifaceted approach that includes algorithmic assessment, real-time system feedback, and operational relevance.

## X. LATEST TRENDS AND RESEARCH IN MRTD OPTIMISATION

Minimum Resolvable Temperature Difference (MRTD) remains a critical parameter for evaluating the thermal resolution of infrared imaging systems. As of 2025, substantial advancements in measurement techniques and thermal sensor technologies are enhancing the accuracy, consistency, and operational relevance of MRTD across a wide range of domains, including defence, environmental monitoring, and industrial diagnostics. Historically, MRTD assessments relied on subjective visual evaluations by human observers, leading to inconsistency and reduced repeatability. Recent developments have introduced objective, algorithm-driven approaches—most notably the use of Adaptive Neuro-Fuzzy Inference Systems (ANFIS). This computational model integrates neural networks with fuzzy logic to emulate human visual perception, offering enhanced precision and eliminating operator bias. In parallel, performance assessments of infrared sensors have become more granular. Comparative analyses of infrared thermal detectors (ITDs) and infrared photonic detectors (IPDs) operating across different spectral bands have shown that ITDs provide superior MRTD performance in the mid-wave infrared (MWIR) region, whereas IPDs are more effective in the long-wave infrared (LWIR) range. Furthermore, MRTD values are influenced by spatial frequency and ambient temperature; specifically, MRTD tends to increase with both parameters, highlighting the need for environment-specific system calibration. Technological convergence with Artificial Intelligence (AI) and the Internet of Things (IoT) is further revolutionizing the domain. AI-enhanced thermal imaging systems can autonomously detect anomalies, adapt imaging parameters in real-time, and extract meaningful features from complex thermal environments. IoT integration enables remote diagnostics and continuous thermal data streaming, enhancing the utility of MRTD measurements in industrial asset monitoring and predictive maintenance. Advancements in detector hardware are also notable. While cooled infrared detectors continue to offer superior sensitivity and lower MRTD values, recent innovations in cryogenic miniaturization and power efficiency are making them more viable for compact platforms. Uncooled detectors, on the other hand, have seen improvements in thermal stability and noise reduction, making them increasingly suitable for portable and tactical systems. The adoption of multispectral and hyperspectral imaging systems, integrating thermal, visible, and ultraviolet bands, is extending MRTD applications to domains such as precision agriculture, environmental surveillance, and biomedical diagnostics. These systems can discern subtle differences in emissivity and material composition, thereby enhancing scene interpretation and target recognition. On the national stage, countries like India are deploying MRTD-reliant technologies for strategic and civilian purposes. The Indian Space Research Organisation's Electro Optical-Infrared (EOIR) payload aboard the EOS-08 satellite supports high-resolution thermal imaging for resource mapping, wildfire detection, and urban planning. Simultaneously, the Indian Army's integration of advanced Hand-Held Thermal Imagers (HHTIs) strengthens its surveillance capabilities, particularly in low-visibility environments. To ensure consistency in system evaluation, the ASTM E1213-14(2022) standard continues to provide a robust framework for MRTD measurement. This standard outline uniform procedures for determining system performance under controlled conditions, thereby supporting cross-platform benchmarking and quality assurance.

## XI. CONCLUSION AND FUTURE OUTLOOK

The future of Minimum Resolvable Temperature Difference (MRTD) research is set to redefine the landscape of thermal imaging, with a strong shift towards adaptive, intelligent, and highly integrated systems. Demands from sectors such as defence, aerospace, healthcare, and industry are driving the need for ultra-low MRTD values to support reliable detection, recognition, and identification in complex environments. At the core of this advancement lies the convergence of quantum sensing, machine learning algorithms, and embedded diagnostic frameworks, collectively enabling real-time adaptability, fault detection, and performance optimisation. Quantum sensors, harnessing quantum mechanical principles, offer significant improvements in sensitivity and resolution, making them ideal for operation in noise-prone or low-signal scenarios. Combined with machine learning, these systems can self-optimise, adjusting resolution, reducing noise, and processing data contextually. This marks a transition from static to

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dynamic MRTD evaluation, where performance continuously adapts based on environmental and operational parameters. Despite these advancements, challenges persist. Standardised testing protocols must evolve to accommodate AI-driven and quantum-enhanced systems. Moreover, achieving environmental robustness and miniaturisation without performance compromise will require continued innovation in materials, embedded technologies, and algorithm design. However, for miniaturization, the adoption of an indigenous solution will greatly strengthen field-level maintenance and operational readiness. By providing technicians with a simple, lightweight, and portable test station, universally compatible across a wide spectrum of thermal imaging devices, it eliminates the need for multiple, device-specific test setups. This kind of standardisation will not only enhance the testing efficiency but also ensure faster fault isolation, reduced downtime, and improved sustainability of critical electro-optical assets in forward areas. In addition, the compact and modular design reduces logistic burden, eases transportation, and simplifies training requirements for operators at all levels. Looking ahead, the solution offers a scalable framework that can be seamlessly adapted to accommodate future generations of sensors and imaging systems, thereby ensuring long-term relevance. Thus, it represents not only a step towards immediate self-reliance but also an investment in the sustained technological autonomy of defence forces. Looking ahead, MRTD will no longer function merely as a metric but as an embedded, adaptive capability—integral to the next generation of smart, high-performance thermal imaging platforms.

## CONTRIBUTORS

Kabir Kohli earned his B.Tech. in Electronics and Communication Engineering from U.P. Technical University, India, and an M.Tech in Optoelectronics & Optical Communication from the esteemed Indian Institute of Technology, Delhi, in 2020. With over 10,000 hours of incident- and accident-free experience in rotary-wing maintenance, he is a highly accomplished aviation maintenance specialist, recognized for his technical proficiency, leadership in maintenance operations, and in-depth knowledge of platform-specific systems. His expertise spans multiple disciplines, having led various projects across diverse domains. His primary areas of expertise encompass lasers, sensors, unmanned aerial systems (drones), nanotechnology, and quantum physics. He is presently serving as an instructor in the Department of Optronics, Gujarat, where he contributes his knowledge and experience to the advancement of optoelectronics, communication, and related technologies.

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