

Controlled Infrared Thermography Dataset for Quantitative Nondestructive Evaluation of Electrical Cable Thermal States

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Research Article

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Abstract

Infrared thermography is widely employed in nondestructive evaluation (NDE) for condition monitoring of electrical infrastructures. Reliable benchmarking of thermographic state discrimination, however, requires controlled and reproducible datasets that capture both equilibrium and transitional thermal regimes. This study introduces a controlled infrared thermography dataset designed for quantitative nondestructive evaluation of electrical cable thermal states.

The dataset was acquired under standardized laboratory conditions using fixed imaging geometry, controlled heating durations, and stable environmental settings to ensure measurement consistency. Three geometric cable configurations (straight, U-shaped, and coiled) were considered to account for spatial variability in heat distribution. Four thermographic states—Cold, Warm, Hot, and Cooling—were defined to represent equilibrium, progressive heating, steady-state accumulation, and transient thermal decay regimes. The final dataset consists of 628 thermographic images, with 157 samples per state.

Unlike many application-specific collections that emphasize extreme fault conditions, the proposed dataset explicitly incorporates gradual thermal transitions, enabling realistic evaluation of thermographic separability and anomaly-level discrimination within a quantitative NDE framework. A baseline validation experiment was conducted to assess thermographic state distinguishability, demonstrating high separability while preserving physically consistent overlap between adjacent transitional states.

The dataset provides a structured and reproducible benchmark for infrared-based cable inspection and is intended to support future research in thermographic state characterization, anomaly detection, and data-driven nondestructive evaluation of electrical systems.

1. Introduction

Thermal behavior monitoring of electrical cables is a critical issue in electrical engineering and plays a significant role in nondestructive evaluation (NDE) and condition monitoring of electrical infrastructures [1]. Abnormal temperature variations may indicate overloading, insulation degradation, increased contact resistance, or early-stage failure mechanisms. Early detection of such conditions is essential for ensuring system reliability, preventing energy losses, and avoiding hazardous situations such as overheating or fire [2, 3]. In this context, infrared (IR) thermography has emerged as a non-contact and effective technique for quantitative analysis of temperature distributions in electrical components without interrupting operation [4].

In recent years, machine learning and deep learning approaches have been widely applied to thermal image analysis for condition monitoring and fault detection [5, 6]. However, the effectiveness of such data-driven inspection frameworks depends strongly on the availability of well-structured, annotated, and reproducible datasets. Despite the growing interest in infrared thermography for electrical diagnostics, there remains a significant lack of publicly available datasets specifically designed for controlled and quantitative analysis of electrical cable thermal states [7]. Existing datasets often suffer from

uncontrolled acquisition conditions, limited class definitions, or overly simplified scenarios that do not adequately represent gradual thermal transitions encountered in practical NDE applications.

From a nondestructive evaluation perspective, one of the key challenges in thermal image-based analysis is the presence of intermediate states, where temperature changes occur gradually rather than abruptly [8]. Many thermographic fault detection studies focus primarily on clearly separable extreme conditions [9]. In real-world inspection scenarios, however, thermal states such as warming and cooling phases exhibit subtle temperature gradients and overlapping spatial distributions, making characterization inherently more complex. While infrared-based cable monitoring studies have demonstrated the feasibility of thermal fault detection [10, 11], systematic representation of transitional thermal states suitable for quantitative benchmarking remains limited.

To address this limitation, this study introduces a controlled infrared thermography dataset specifically designed for quantitative nondestructive evaluation of electrical cable heating conditions. The dataset is generated under standardized experimental conditions, including fixed camera positioning, consistent environmental background, and controlled heating durations using an electrical load. In addition, multiple cable configurations are considered to introduce structural variability, while four distinct thermal states—Cold, Warm, Hot, and Cooling—are defined to capture both stable and transitional thermal behaviors representative of practical monitoring scenarios.

The primary contribution of this work is the development of a reproducible and balanced thermographic dataset that not only includes clearly distinguishable states but also incorporates gradual thermal transitions between adjacent conditions. This design enables more realistic evaluation of data-driven analysis methods while maintaining alignment with quantitative NDE principles. A baseline deep learning experiment is provided to demonstrate the usability of the dataset and to establish a reference performance for future comparative studies.

Overall, the proposed dataset aims to fill a critical gap in thermographic inspection research by providing a structured, controlled, and application-oriented benchmark for quantitative evaluation of electrical cable thermal states. It is expected to facilitate further advancements in condition-based maintenance, predictive monitoring, and intelligent nondestructive inspection systems.

2. Related Works

Infrared thermography has long been recognized as a practical non-contact technique for nondestructive evaluation (NDE) of electrical and electromechanical systems [12]. Its ability to capture spatial temperature distributions without physical contact makes it particularly suitable for detecting abnormal thermal behavior associated with insulation degradation, overload conditions, contact resistance increases, and early-stage defect formation. Early studies primarily relied on handcrafted feature extraction and conventional machine learning to classify faults from thermal patterns [13], demonstrating that infrared imagery could support condition assessment and preventive maintenance strategies in electrical facilities and other energy-related infrastructures.

With the rapid development of deep learning, the focus gradually shifted from manual feature engineering toward automatic representation learning [14]. In power-system applications, infrared images have been used for fault detection in electrical facilities and intelligent diagnosis of overheating regions in substations, illustrating the growing integration of thermography with data-driven inspection systems [15]. These approaches have significantly improved automation capabilities in NDE-based monitoring of electrical assets.

Cable-related thermographic inspection has received comparatively less attention. Li et al. proposed an infrared image-based state evaluation method for cables using deep learning [16], while Mu et al. investigated autonomous diagnosis of overheating defects in cable accessories through object detection and thermal analysis [17]. Although these studies confirm the relevance of infrared thermography for cable condition monitoring, they are primarily oriented toward fault detection tasks rather than the development of reproducible, balanced datasets explicitly structured for quantitative benchmarking.

Beyond cable systems, infrared thermography has been widely applied in rotating machinery, industrial manufacturing, and infrastructure diagnostics. Dos Santos et al. employed transfer learning for electric motor fault diagnosis using thermographic images [18]. Atif et al. combined conventional and deep learning strategies for induction motor inspection [19]. Similarly, Buongiorno et al. demonstrated the effectiveness of thermographic image processing for inline defective weld identification in manufacturing environments [20]. These works collectively reinforce the role of infrared imaging as a core tool in modern nondestructive inspection frameworks.

In electrical infrastructure monitoring, recent transfer-learning studies further highlight the potential of thermographic analysis. Elgohary et al. applied CNN-based classification to thermal images from transformer rooms [21], while Liu et al. proposed abnormal heating detection methods for high-voltage equipment operating under visually complex conditions [22]. Object-detection-based thermographic approaches have also expanded rapidly. Several recent studies have constructed infrared datasets for substation equipment and evaluated detection performance using advanced deep learning frameworks under diverse operating conditions [23]. Wu et al. reported YOLO-based detection of power equipment from thermal images [24]. These studies reflect the transition from manual thermal inspection toward automated and intelligent NDE systems.

Photovoltaic (PV) inspection represents another significant application domain. Infrared thermography has been extensively used to detect hot spots and defective modules [25]. Jaffery and Dubey proposed early thermography-based fault diagnosis for solar modules, and subsequent works evaluated machine learning and deep learning techniques for PV fault detection from thermal images [26]. Recent review articles confirm the methodological maturity of combining thermography and deep learning in energy-related inspection tasks [27].

Thermal imaging has also been extended to broader infrastructure and industrial systems. Several studies have demonstrated the effectiveness of infrared thermography for fault diagnosis in rotating

machinery, including induction motors and gearboxes, using data-driven and deep learning-based approaches [28]. In large-scale infrastructure environments, thermographic inspection has been adopted for monitoring electrical installations, transportation systems, and industrial assets under real operating conditions [29]. Furthermore, comprehensive review studies emphasize that intelligent fault detection frameworks for power equipment increasingly rely on multimodal sensing and machine learning integration, where thermography serves as a key modality for anomaly detection and predictive maintenance [30].

Thermal imaging has also been extensively applied across broader infrastructure and industrial systems. In addition to rotating machinery and manufacturing processes, infrared thermography has been employed for condition assessment in large-scale electrical and mechanical installations [31]. Recent studies demonstrate its applicability in non-invasive fault diagnosis and structural inspection under real operating conditions. Moreover, recent studies highlight the integration of thermography with multimodal sensing and data-driven diagnostic frameworks, demonstrating its expanding role in intelligent anomaly detection and predictive maintenance of industrial and power systems [32].

Despite these advancements, an important gap remains in the context of quantitative nondestructive evaluation. Much of the existing literature focuses on task-specific fault detection rather than on publishing controlled, balanced, and reproducible thermographic datasets tailored for benchmarking and methodological development [33]. Even cable-related studies tend to emphasize defect identification in accessories rather than systematic characterization of multi-state thermal behavior under standardized acquisition conditions [34].

From a quantitative NDE standpoint, two limitations are particularly evident. First, reproducible benchmarking requires experimentally controlled and clearly annotated image collections rather than proprietary datasets tied to specific applications [35]. Second, realistic thermal monitoring must account for gradual temperature evolution, including transitional heating and cooling phases, which are inherently more challenging to characterize than extreme conditions [36]. While prior studies strongly support the value of infrared thermography for electrical diagnostics, there remains a clear need for datasets that explicitly capture multi-state thermal behavior in cable systems under controlled and repeatable conditions.

3. Dataset Description

3.1 Overview of the Dataset

The proposed dataset consists of infrared thermographic images acquired under controlled laboratory conditions to represent multiple thermal states of electrical cables for quantitative nondestructive evaluation. The dataset is structured to enable systematic characterization of both stable and transitional thermal behaviors, reflecting realistic heating and cooling processes encountered in practical cable monitoring scenarios.

A total of 628 thermal images were selected from an initial pool of 664 raw images, ensuring a balanced distribution of 157 images per thermal state. Four distinct thermal states are defined: Cold, Warm, Hot, and Cooling. These states were established to represent equilibrium and transient thermal conditions that may correspond to different operational or anomaly levels in cable systems.

Rather than focusing solely on separable extreme conditions, the dataset intentionally incorporates intermediate thermal transitions to support realistic evaluation of thermographic state discrimination and anomaly characterization within a quantitative NDE framework.

3.2 Experimental Setup and Data Acquisition

The dataset was generated using a controlled laboratory setup designed to ensure repeatability and measurement consistency for quantitative infrared thermographic evaluation. The overall acquisition framework is illustrated in Fig. 1.

A controllable electrical heating source was used to induce temperature variations along the cable surface in a reproducible manner. The heating duration was carefully regulated to produce predefined thermal states corresponding to equilibrium and transient conditions.

During the experiments, an infrared thermal camera was positioned approximately 50 cm above the cable in a near top-down configuration to minimize perspective distortion and ensure uniform spatial resolution. The camera position and focal distance were kept fixed throughout all acquisitions to maintain geometric consistency across samples.

All recordings were performed under stable ambient laboratory conditions. A uniform background with low thermal reflectivity was used to reduce environmental interference and unwanted reflections. The emissivity setting of the thermal camera was kept constant during all measurements to preserve temperature-scale consistency across different thermal states.

The combination of fixed acquisition geometry, controlled heating duration, and stable environmental conditions enables the dataset to serve as a reproducible benchmark for quantitative thermographic analysis within a nondestructive evaluation framework.

3.3 Cable Configurations and Thermal States

To account for geometric variability and its influence on heat distribution patterns, three distinct cable configurations were considered, as illustrated in Fig. 2. In thermographic nondestructive evaluation, geometric arrangement can significantly affect apparent temperature gradients, heat accumulation zones, and spatial radiation characteristics [37]. Therefore, incorporating multiple structural configurations enhances the robustness and realism of the dataset.

The cable configurations are defined as follows: S1 represents a straight cable, S2 corresponds to a U-shaped cable, and S3 denotes a coiled cable. These configurations were selected to reflect realistic variations in cable placement and their impact on thermal distribution patterns.

In addition to geometric variation, four thermal states were defined based on controlled heating duration and the corresponding thermographic response of the cable surface. These states represent both equilibrium and transient thermal regimes encountered in practical monitoring scenarios:

- **Cold (C0):** Cable in idle condition with no external heating applied, representing baseline thermal equilibrium.
- **Warm (C1):** Cable subjected to 20 seconds of controlled heating, corresponding to an initial temperature rise and early-stage thermal gradient formation.
- **Hot (C2):** Cable subjected to 60 seconds of continuous heating, representing a higher steady-state temperature distribution and more pronounced spatial heat accumulation.
- **Cooling (C3):** Cable recorded after heating followed by 40 seconds of passive cooling, corresponding to a transient thermal decay phase.

Rather than defining states solely by heating duration, each class reflects a distinct thermographic pattern characterized by relative temperature distribution and spatial heat dissipation behavior. By incorporating both clearly distinguishable conditions (Cold and Hot) and intermediate transitional states (Warm and Cooling), the dataset captures gradual thermal evolution processes relevant to quantitative nondestructive evaluation.

The dataset is structured to ensure statistical consistency across defined thermal states, with an equal number of samples acquired under controlled experimental conditions for each configuration and thermal regime. This balanced acquisition protocol minimizes sampling bias and enables reproducible quantitative comparison of thermographic patterns across states. The final dataset consists of 628 thermographic images, with 157 samples per thermal state.

The structured and controlled composition of the dataset supports benchmarking of thermal-state discrimination, anomaly-level differentiation, and robustness analysis within a quantitative nondestructive evaluation framework.

4. Baseline Validation Experiment

To quantitatively evaluate the discriminability of the defined thermographic cable states within a nondestructive evaluation framework, a baseline validation experiment was conducted. The purpose of this analysis was not to introduce a novel classification methodology, but to examine whether the controlled acquisition protocol produces sufficiently distinct thermal signatures across equilibrium and transitional conditions.

A pre-trained convolutional neural network (GoogLeNet) was employed as a standardized pattern recognition tool to assess thermographic state separability. Transfer learning was applied by modifying the final classification layer while preserving the generic feature extraction layers. The dataset was

partitioned into training, validation, and test subsets under statistically balanced conditions to avoid sampling bias.

The resulting classification performance is interpreted here as an indicator of quantitative thermographic separability rather than as an optimization study of machine learning architectures. This baseline assessment establishes a reproducible reference level for future comparative investigations in thermographic nondestructive evaluation.

5. Thermographic State Discrimination Analysis

To examine the quantitative separability of thermographic signatures corresponding to the defined cable states, the baseline validation experiment was evaluated on the independent test subset.

The obtained test discrimination accuracy of 98.95% indicates that the controlled acquisition protocol yields thermographic patterns that are statistically distinguishable across equilibrium and transitional thermal regimes. This result is interpreted as a measure of thermographic state separability rather than as an optimization of a classification architecture.

The confusion matrix (Fig. 3) demonstrates clear separation among most states, with minimal overlap observed between adjacent thermal conditions. The single misclassification occurred between the Warm and Hot states, which represent consecutive heating phases. This outcome is physically consistent with the gradual evolution of temperature gradients and spatial heat accumulation during progressive heating.

The Cold and Cooling states exhibited complete separability in the test subset. The Cold condition represents ambient thermal equilibrium, whereas the Cooling state reflects transient post-heating thermal decay. The clear distinction between these regimes confirms that the dataset captures meaningful thermographic signatures beyond absolute temperature magnitude, including spatial heat dissipation behavior.

The limited confusion observed between transitional states further supports the dataset's applicability for quantitative nondestructive evaluation scenarios, where subtle thermal variations must be reliably characterized to detect early-stage anomalies or evolving conditions.

Overall, the results demonstrate that the proposed dataset provides a controlled and physically coherent thermographic structure suitable for reproducible state discrimination analysis within a quantitative NDE framework.

6. Discussion

The discrimination performance obtained in the baseline validation experiment indicates that the defined thermal regimes exhibit measurable and statistically distinguishable spatial temperature patterns. The limited confusion observed between the Warm and Hot states is physically consistent with the

progressive nature of heat accumulation. These two conditions correspond to consecutive heating phases, where temperature gradients and surface heat distribution evolve gradually rather than abruptly. The slight overlap between these states reflects realistic thermal evolution behavior, which is expected in practical monitoring scenarios.

In contrast, the clear separability of the Cold and Cooling states suggests that equilibrium and post-heating decay regimes present thermographically distinct patterns. The Cold state represents baseline ambient equilibrium, while the Cooling state corresponds to transient thermal dissipation after sustained heating. The ability to distinguish these regimes indicates that the dataset preserves meaningful thermal dynamics beyond simple temperature magnitude differences.

From a nondestructive evaluation perspective, the inclusion of both equilibrium and transitional thermal conditions enhances the dataset's relevance. In real inspection environments, thermal anomalies rarely manifest as binary states; instead, they develop progressively through intermediate regimes. The structured representation of gradual heating and cooling behavior enables evaluation of sensitivity to early-stage thermal deviations.

Overall, the dataset establishes a reproducible thermographic reference framework for quantitative cable state evaluation, combining statistical separability with physically consistent transitional behavior.

7. Conclusion

This study presented a controlled infrared thermography dataset tailored for quantitative nondestructive evaluation of electrical cable thermal behavior. By systematically incorporating geometric variability and multi-stage thermal evolution, the dataset enables reproducible investigation of thermographic state discrimination under standardized acquisition conditions.

Unlike many application-driven thermographic studies that focus primarily on extreme fault detection, the proposed dataset emphasizes gradual thermal evolution, supporting sensitivity analysis to transitional heating and cooling regimes. The baseline validation experiment confirms that the defined states are statistically distinguishable while preserving physically realistic overlap between adjacent conditions.

The dataset thus provides a structured experimental foundation for future research in quantitative thermographic characterization, anomaly progression analysis, and data-driven NDE methodologies for electrical infrastructures.

Future extensions may integrate additional loading scenarios, environmental variability, or multi-modal sensing to further expand the applicability of the framework in industrial monitoring contexts.

Declarations

Competing Interests

The author declares that there are no competing interests.

Ethics Approval

Not applicable.

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Author Contribution

H.S.N. conceived the study, designed the experimental setup, acquired the thermographic data, performed the analysis, and wrote the manuscript. The author read and approved the final manuscript.

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Data Availability

The thermographic dataset generated in this study will be made publicly available upon acceptance of the manuscript through an open-access repository.

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Figures

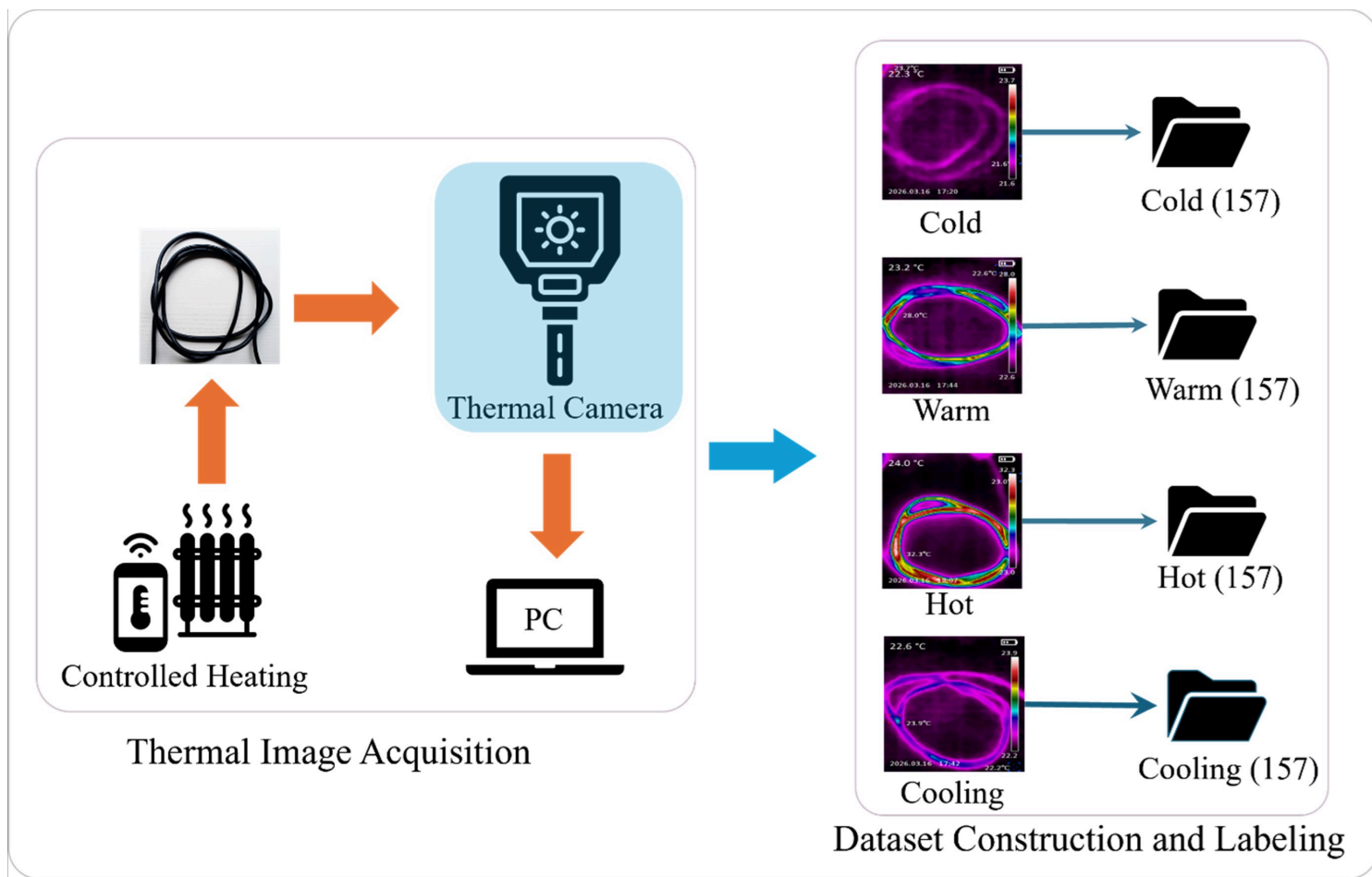


Figure 1

Experimental setup and dataset construction process.

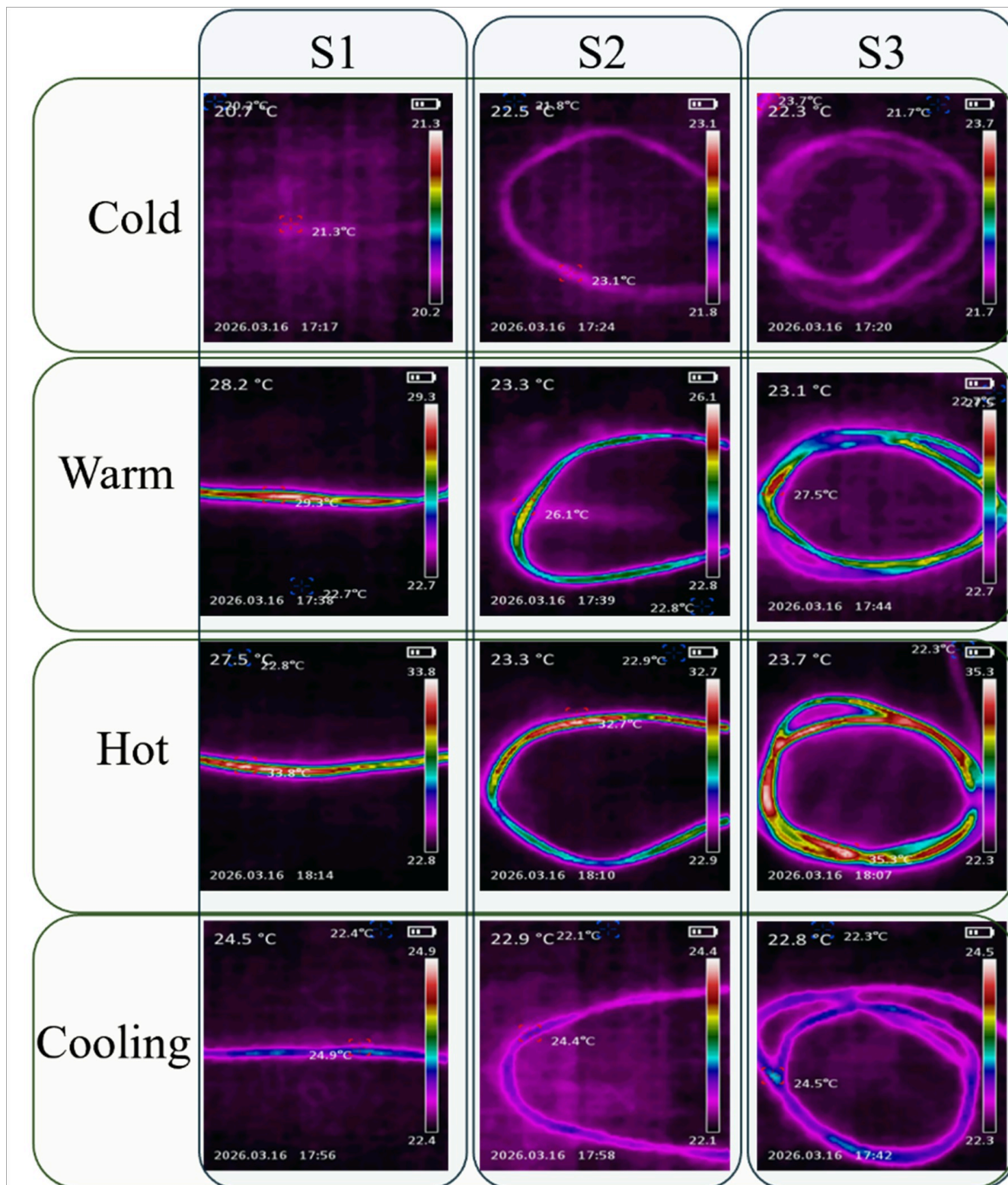


Figure 2

Sample thermal images for different cable configurations (S1–S3) and thermal states (Cold, Warm, Hot, Cooling).

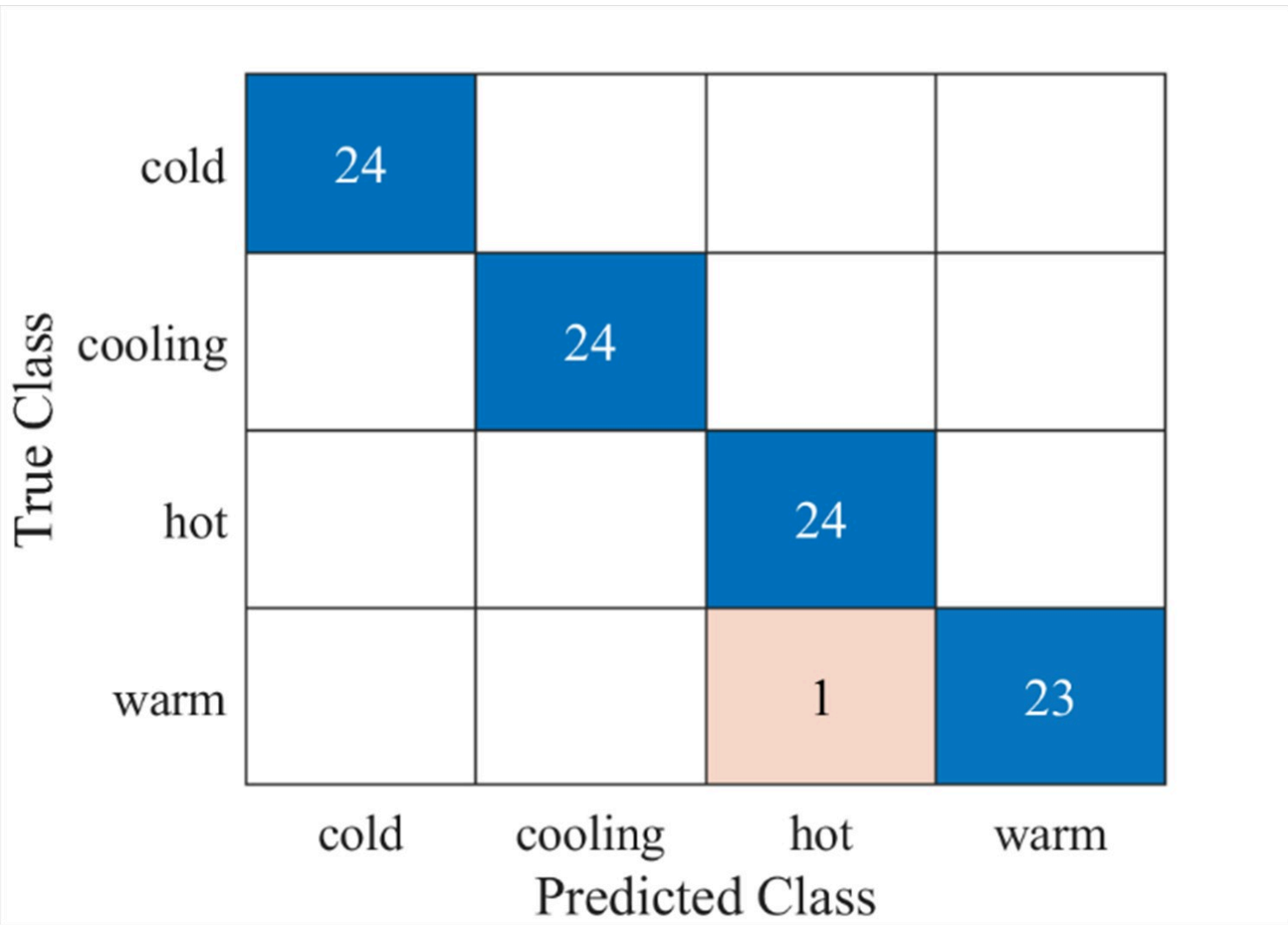


Figure 3

Confusion matrix obtained from the test set for the four-class classification task.