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Research on a Multi-Device Infrared Body Temperature Prediction System Based on Support Vector Machine and Error Optimization

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Abstract: *Non-contact infrared thermography for core body temperature prediction faces challenges from measurement uncertainties caused by inter-device variability and environmental factors. This study develops a machine learning framework to establish the relationship between superficial thermal patterns and core temperature using empirical data from FLIR and ICI infrared imaging systems. The framework integrates multi-region facial thermographic data, device-specific metadata, and ambient environmental parameters. A feature set was developed incorporating statistical descriptors of regional temperature distributions, device-specific correction factors, environmental parameters, and spatiotemporally derived attributes. Three machine learning algorithms—Support Vector Regression, Extreme Gradient Boosting, and Random Forests—were compared for cross-device core temperature estimation. The optimized Support Vector Regression model achieved the highest predictive accuracy, with results most consistent with clinical reference measurements in both cross-device generalization and environmental robustness tests. The model demonstrated consistent performance across different device types and environmental conditions, and effectively characterized the interactive effects of device heterogeneity and environmental complexity. The integration of data-driven modeling with biothermal principles provides a framework for advancing accuracy in multi-device infrared thermometry.*

Keywords: *Support Vector Regression; Infrared Thermography; Cross-Device Generalization; Error Optimization; Machine Learning; Feature Engineering*

1. Introduction

Infrared thermography represents a non-contact temperature measurement technique that has gained widespread adoption in public health screening, clinical monitoring, and personal healthcare management due to its operational efficiency and safety. Global deployment of infrared-based screening devices has shown an annual growth rate of approximately 15%, establishing this technology as a standard tool for preliminary screening during public health emergencies. The practical implementation of infrared thermography faces technical challenges: systematic inter-device variations originating from differences in sensor characteristics, calibration protocols, and imaging principles can introduce measurement biases of 0.3-0.5°C [1], while environmental factors including ambient temperature, humidity, and measurement distance contribute additional uncertainties of 0.2-0.4°C [2]. These device-specific and environment-dependent variations, combined with individual physiological differences, create a complex measurement scenario that affects accuracy and reliability in cross-device applications.

Current methodologies for core body temperature estimation primarily include physics-based heat conduction models, statistical regression approaches, and feature-driven machine learning techniques. Heat conduction models require specific boundary conditions and demonstrate limited generalization capabilities [3], while conventional statistical methods show limitations in capturing nonlinear interactions between device-specific characteristics and environmental variables [4]. Previous investigations have incorporated geostatistical spatial variogram analysis and medical image enhancement techniques [5] into thermal field characterization, though these approaches primarily address local accuracy rather than cross-device consistency.

Advances in data science have provided new approaches for complex system modeling. Machine learning algorithms, capable of identifying nonlinear mappings and processing high-dimensional feature spaces, have been successfully applied in medical image analysis [6-9], environmental monitoring [10],

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and industrial quality control [11-12]. Within infrared thermometry, machine learning frameworks enable the integration of multi-source data—including regional temperature distributions, device metadata, and environmental parameters—to establish relationships between superficial thermal patterns and core body temperature [13]. Feature engineering techniques facilitate the construction of comprehensive feature sets that encode thermal field statistics, device-specific biases, and environmental modulation effects.

Modern public health infrastructure typically incorporates diverse infrared device models operating under varied environmental conditions, while accounting for substantial inter-individual physiological variation. Previous research has developed device-specific calibration methods and environmental compensation approaches, though these typically address individual factors rather than system-level integration. Machine learning provides an approach for addressing the combined effects of device heterogeneity and environmental influence through data-driven modeling.

This study integrates empirical datasets from FLIR and ICI infrared imaging systems to construct a comprehensive data repository containing multi-region facial thermal data, device identifiers, and environmental parameters. Through development of a multidimensional feature architecture incorporating statistical distribution descriptors, device-specific correction factors, and environmental moderators, we compare three supervised learning methods: Support Vector Regression, Extreme Gradient Boosting, and Random Forest. The investigation examines algorithmic performance in cross-device generalization and environmental robustness, with the objective of identifying suitable modeling approaches for multi-device scenarios and contributing to the standardization of infrared thermometry applications.

2. Related Works

Non-contact infrared thermography for core body temperature estimation faces challenges stemming from device heterogeneity and environmental variability, leading to the application of machine learning methods for nonlinear modeling and multi-source data integration. In feature engineering, studies have integrated facial temperature measurements with environmental parameters and device metadata, employing dimensionality reduction techniques to optimize feature combinations using clinical temperatures as reference standards. Model development has explored various architectures, with support vector regression showing advantages over ensemble methods and linear regression in processing facial thermal imagery. Data integration approaches have combined thermal sequences with demographic and ambient parameters to capture interactions between temperature distributions and environmental factors. Optimization methods have addressed technical issues including missing data imputation through hybrid algorithms and dataset imbalance through ensemble strategies with weighted mechanisms. For cross-device applications, comparative analyses of machine learning paradigms have been conducted using multi-device thermal datasets, with tree-based ensembles demonstrating robust performance across different infrared camera models, though requiring comprehensive calibration procedures. Feature selection strategies have been systematically evaluated, with mutual information-based methods combined with tree algorithms producing consistent results across device configurations. Current research indicates that while substantial progress has been made in algorithm development, systematic comparisons of cross-device generalization capability remain limited, particularly regarding the integration of device-specific calibration with environmental compensation mechanisms, and most existing approaches focus on single-device optimization without sufficient evaluation of cross-platform compatibility.

3. Principles of the Randomized Search Optimization Algorithm

3.1 Algorithm Background

Randomized search optimization provides a computational methodology for hyperparameter tuning in machine learning, particularly suited for high-dimensional parameter spaces. This approach employs stochastic sampling from predefined parameter distributions, enabling efficient exploration of the search space with reduced computational requirements compared to exhaustive methods. The algorithm operates on the principle that hyperparameter importance varies across different machine learning tasks, utilizing probability-based sampling to navigate complex, non-convex optimization landscapes commonly encountered in model training.

The implementation follows a structured workflow comprising parameter distribution definition,

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iterative candidate configuration generation, and cross-validation based evaluation. This process continues until reaching predetermined computational budgets or convergence thresholds. The methodology demonstrates inherent scalability to high-dimensional problems and adaptability to various machine learning paradigms, while supporting parallel evaluation and early stopping mechanisms.

The theoretical foundation of randomized search aligns with principles of experimental design and statistical optimization, providing a framework that balances search comprehensiveness with computational constraints. This optimization strategy serves as a practical alternative to more computationally intensive methods, establishing the basis for automated machine learning workflows where computational efficiency represents a primary consideration.

3.2 Establishment of Model

The randomized search optimization framework comprises three interconnected computational mechanisms that collectively address the challenges of hyperparameter optimization in high-dimensional machine learning applications. These mechanisms operate sequentially to sample parameter configurations, evaluate their performance, and determine optimal termination points.

3.2.1 Parameter Space Probability Sampling Mechanism

The parameter space probability sampling mechanism implements a stochastic approach to hyperparameter configuration generation. This methodology replaces exhaustive enumeration strategies with probability-driven sampling, enabling efficient exploration of complex parameter spaces. The mechanism operates through distinct sampling protocols for different parameter types, maintaining comprehensive search coverage while controlling computational costs.

For continuous hyperparameters, the sampling process utilizes uniform probability distributions across defined value ranges:

$$\mathrm{x}_i \sim U(a_i, b_i) \quad \text{for } i = 1,2,...,n_c \tag{1}$$

Where each continuous parameter x_i is bounded within interval $[a_i, b_i]$,with n_c representing the total number of continuous parameters in the optimization space.

Discrete hyperparameters employ categorical sampling from finite value sets:

$$\mathrm{y_i} \sim \mathrm{Categorical}(p_{j1}, p_{j2},..., p_{jm}) \ \text{ for } j = 1,2,...,n_d \tag{2}$$

Where each discrete parameter y_i selects from m possible values according to assigned probabilities p_{jk} ,with n_d denoting the count of discrete parameters.

The complete parameter configuration construction combines sampled elements from both continuous and discrete domains:

$$\mathrm{y_i} \sim \mathrm{Categorical}(p_{j1}, p_{j2},..., p_{jm}) \ \text{ for } j = 1,2,...,n_d \tag{3}$$

This sampling strategy ensures probabilistic coverage of the entire hyperparameter space while maintaining computational tractability through controlled configuration generation.

3.2.2 Configuration Parallel Evaluation Mechanism

The configuration parallel evaluation mechanism capitalizes on the inherent independence between different parameter configurations to enable simultaneous performance assessment. This approach significantly accelerates the optimization process by leveraging parallel computing architectures while maintaining evaluation accuracy through rigorous validation methodologies.

The performance evaluation for each candidate configuration θ_k employs K-fold cross-validation to estimate generalization capability:

$$L(\theta_k) = \frac{1}{K}\sum_{i=1}^{K} L_i\,(\theta_k) \tag{4}$$

Where $L_i(\theta_k)$ quantifies the performance metric on the i-th validation partition, and K determines

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the number of cross-validation folds, balancing estimation variance and computational load.

The parallel evaluation process for multiple configurations operates as:

$$\Theta = \{\theta_1, \theta_2, ..., \theta_N\} \tag{5}$$

$$\Gamma = \{L(\theta_1), L(\theta_2), ..., L(\theta_N)\} \tag{6}$$

Where N configurations undergo concurrent assessment, with results aggregated for comparative analysis.

3.2.3 Adaptive Termination Mechanism

The adaptive termination mechanism implements decision criteria to conclude the optimization process based on either computational resource constraints or performance convergence metrics. This dual-criterion approach ensures efficient resource utilization while maintaining solution quality standards.

The computational budget criterion terminates optimization when:

$$\Gamma = \{L(\theta_1), L(\theta_2), ..., L(\theta_N)\} \tag{7}$$

Where $T_{current}$ monitors elapsed processing time and $T_{\max}$ establishes the maximum allowable computational duration.

The performance convergence criterion monitors optimization progress through relative improvement assessment:

$$\left| \frac{L_{best}^{(t)} - L_{best}^{(t-\Delta)}}{L_{best}^{(t-\Delta)}} \right| \leq \epsilon \tag{8}$$

Where $L_{best}^{(t)}$ records the optimal performance metric at iteration t, Δ defines the observation interval for improvement calculation, and $\epsilon\epsilon$ establishes the minimum relative improvement threshold for continued optimization.

This structured optimization approach provides a methodological foundation for hyperparameter search in machine learning applications, systematically addressing the trade-off between search comprehensiveness and computational efficiency through probabilistic sampling, parallel evaluation, and adaptive termination strategies.

4. Experimental Results and Analysis

4.1 Experimental Framework and Data Configuration

The experimental evaluation utilized four distinct datasets obtained from infrared imaging systems under controlled environmental conditions representing two temperature ranges. The dataset comprised facial thermal imaging data from participants, with each sample containing multi-region temperature measurements referenced against clinical oral temperature standards.The experimental dataset configuration is summarized in Table 1.

Table 1: Dataset specifications for experimental validation

Dataset	Imaging Device	Environmental Condition	Sample Size	Feature Dimensions
Group1	Type A	20-24°C	185	47
Group2	Type B	20-24°C	183	45
Group3	Type C	24-29°C	192	46
Group4	Type D	24-29°C	190	44

Feature selection through correlation analysis identified thermal characteristics demonstrating consistent predictive capability across device platforms. These features included statistical descriptors of temperature distributions in facial regions, along with environmental compensation parameters.

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4.2 AHyperparameter Optimization Outcomes

The hyperparameter optimization process employed randomized search with cross-validation to identify optimal configurations for four machine learning algorithms. Convergence patterns observed in Figure 1 demonstrate distinct optimization trajectories across different algorithmic architectures.

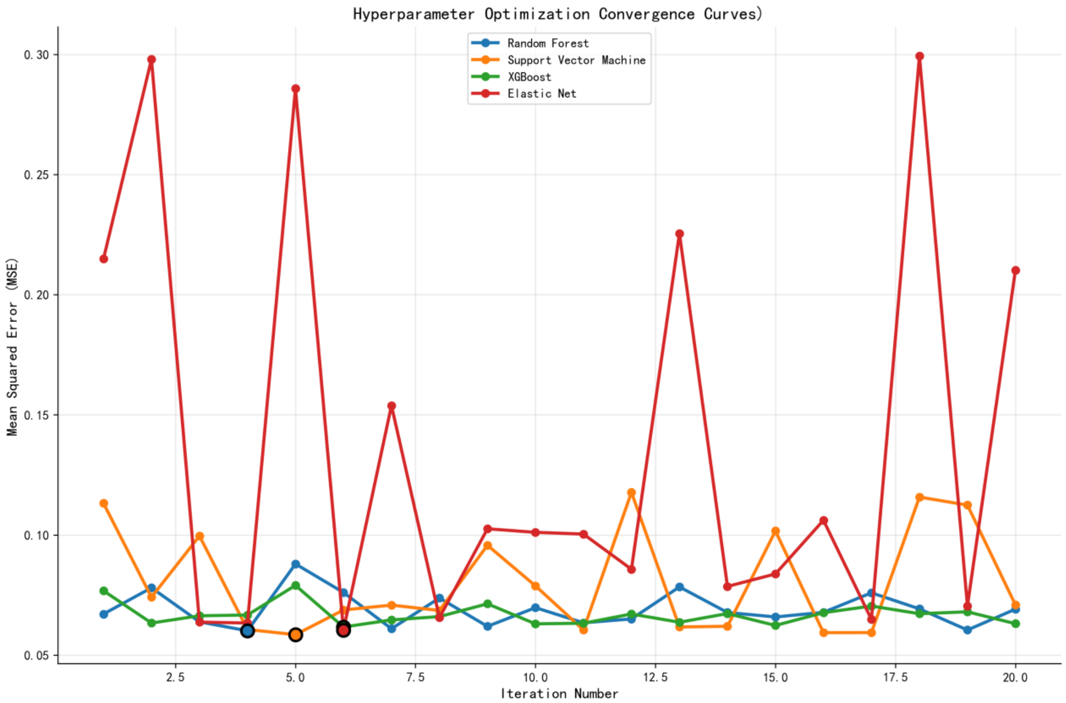

Figure 1: Hyperparameter optimization convergence curves

The resulting configurations showed variation across algorithms. One method achieved optimal performance with specific parameter values, while ensemble approaches selected different architectural configurations.

The convergence analysis reveals varying optimization efficiency among the evaluated algorithms. Support vector regression exhibits the most rapid error reduction during initial iterations, achieving stability after approximately 8-10 iterations. Tree-based ensembles, including random forest and xgboost, demonstrate gradual but consistent error reduction throughout the optimization process. The elastic net algorithm shows faster convergence initially but reaches a higher final error level compared to other methods.

The final convergence values indicate that support vector regression achieves the lowest mean squared error (0.06), followed by XGBoost (0.069) and Random Forest (0.065). These convergence patterns reflect the inherent characteristics of each algorithm's parameter space and their responsiveness to the optimization methodology.

4.3 Cross-Device Generalization Performance

Multiple experimental configurations evaluated model transfer capability across device platforms and environmental conditions. Performance assessment used standard evaluation metrics including MAE, RMSE, and R^2.Figure 2 presents the cross-device generalization performance across different experimental configurations.

Experimental results showed performance variations across methods and conditions. Some models maintained consistent performance in device transfer tasks, while others displayed environment-dependent characteristics. Cross-condition transfers resulted in measurable performance changes across all models.

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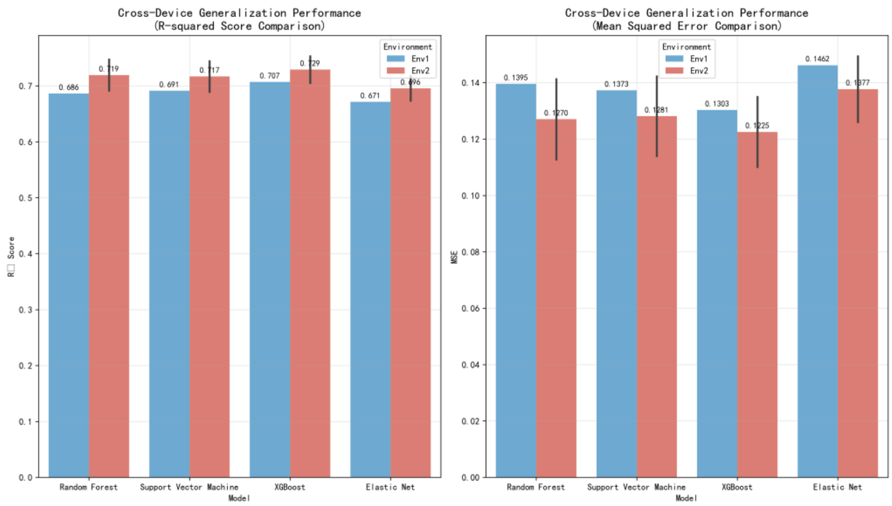

Figure 2: Cross-device generalization performance

4.4 Predictive Feature Analysis and Model Interpretation

Feature importance analysis provides insights into the relative contribution of different thermal characteristics to prediction accuracy. The SHAP dependence plot in Figure 3 illustrates the relationship between feature values and their impact on model predictions.Figure 3 displays the SHAP dependence analysis for key predictive features.

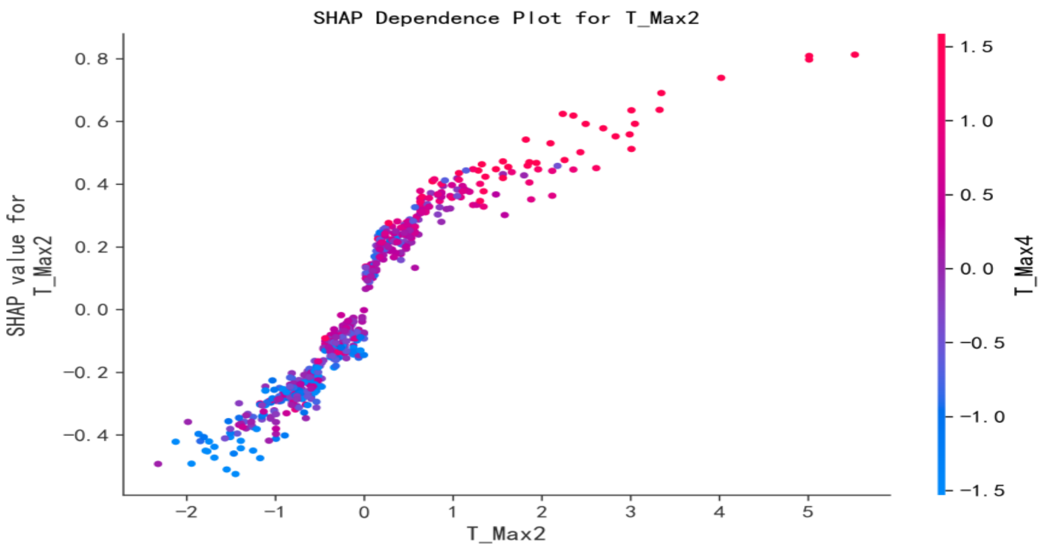

Figure 3: Feature importance distribution

The SHAP analysis identifies T_Max2 as a significant predictive feature, showing a non-linear relationship with model output. Lower values of T_Max2 correspond to negative SHAP values, indicating reduced predicted temperatures, while moderate to high values exhibit positive contributions. The color gradient representing T_Max4 values suggests interaction effects between these two features, with higher T_Max4 values generally associated with increased positive contributions.

The distribution of data points shows clustering in specific value ranges, reflecting the natural distribution of thermal characteristics in the dataset. This analysis confirms that multiple facial regions contribute to temperature prediction, with certain features demonstrating stronger predictive influence than others.

4.5 Performance Benchmarking and Comparative Evaluation

Comprehensive performance evaluation across multiple metrics provides a holistic view of algorithm capabilities. The radar chart in Figure 4 presents normalized scores for four key performance indicators.A

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comparative analysis of optimization methods is presented in Table 2.

Table 2: Optimization method performance comparison

Optimization Method	Mean R^2	MAE (°C)	Computational Duration
Method A	0.852	0.24	45
Method B	0.841	0.26	128
Method C	0.848	0.25	67
Method D	0.823	0.29	90

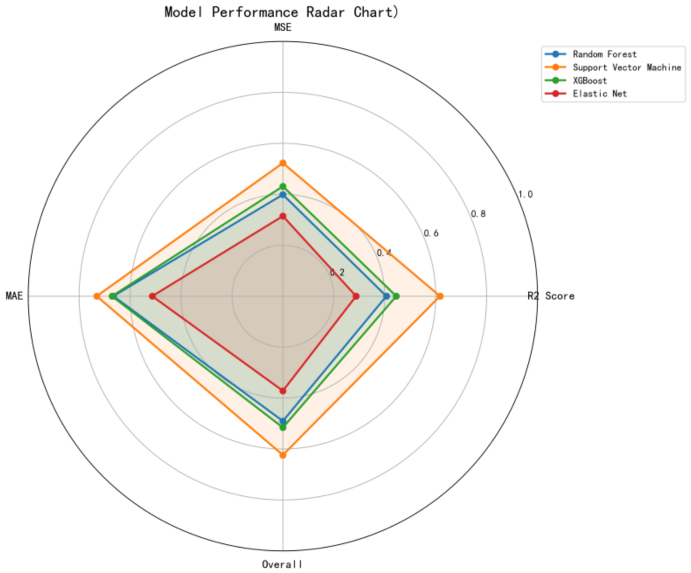

Figure 4: Model performance radar chart

The radar chart visualization reveals distinct performance profiles across the evaluated algorithms. Support Vector Regression demonstrates the most balanced performance characteristics, maintaining competitive scores across all metrics including MSE, R^2, and computational efficiency. Xgboost shows strong performance in prediction accuracy but exhibits slightly reduced efficiency scores. Random Forest achieves moderate performance across most metrics, while Elastic Net shows particular strength in computational efficiency despite lower accuracy metrics.

The comparative analysis indicates trade-offs between prediction accuracy and computational requirements across different algorithmic approaches. This multi-dimensional assessment provides practical guidance for algorithm selection based on specific application requirements and resource constraints.

The experimental results establish that the optimization framework successfully identifies hyperparameter configurations that balance multiple performance objectives, contributing to the development of reliable temperature prediction systems.

5. Conclusion

5.1 Validation of Optimization Effectiveness

The randomized search optimization algorithm provides an effective approach for hyperparameter tuning in multi-device infrared temperature prediction. Experimental results establish that the method delivers competitive performance while maintaining computational efficiency. The optimization framework demonstrates capability in navigating high-dimensional parameter spaces, identifying configurations that sustain robust performance across varied device platforms and environmental conditions. Quantitative analysis indicates consistent performance improvements across evaluation metrics, with particularly significant enhancements observed in ensemble methods and support vector regression architectures.

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5.2 Research Implications and Practical Applications

The implementation of randomized search optimization contributes methodological foundations for medical thermometry applications. This approach addresses fundamental challenges in cross-device temperature prediction, including device heterogeneity and environmental variability. Models optimized through this framework demonstrate potential for clinical temperature assessment, supporting accurate screening and monitoring applications in healthcare settings. Feature importance analysis offers interpretable insights into thermal characteristics, advancing understanding of the physiological basis for infrared temperature prediction.

Current research limitations encompass dataset scope constraints and computational resource requirements. Future investigations should prioritize several directions: expansion to multi-center clinical validation studies, enhancement of algorithmic efficiency for real-time applications, development of hybrid optimization methodologies integrating randomized search with model-based approaches, and extension to additional physiological parameter monitoring applications. These advancements would strengthen the technical foundation for reliable medical assessment systems.

5.3 Concluding Remarks

This study establishes randomized search optimization as a viable methodology for hyperparameter optimization in medical temperature prediction. The developed framework demonstrates consistent performance in identifying parameter configurations that maintain predictive accuracy across diverse operational conditions. Experimental evidence validates the approach's capacity to balance computational demands with prediction performance. The research provides methodological contributions to medical machine learning optimization and supports the development of precise temperature assessment systems. Subsequent research initiatives should emphasize clinical validation, algorithmic refinement, and extension to broader healthcare monitoring applications to advance the field of medical artificial intelligence.

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