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A Deep Learning Framework for Multi-Sensor Thermal Comfort Prediction in Passenger Cars

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ABSTRACT

Using a combination of environmental and physiological sensors to gather real-time data on the cabin's circumstances and the occupants' responses, a useful deep learning framework is created to predict the comfort and stress levels of passengers in a passenger car cabin. This system analyses the intricate relationships between a number of variables, including temperature, humidity, airflow, and occupant biometrics, using advanced deep learning algorithms. This makes it possible for it to estimate thermal comfort levels and possible heat stress in a precise and dynamic manner. Passengers' health, safety, and comfort during travel can be improved by integrating the system into passenger cars to enable proactive climate control modifications. It tackles issues brought on by shifting environmental circumstances and individual differences in heat sensitivity. This is an example of how AI-driven sensor fusion might improve human-centered climate control in automobiles.

Keywords

Sensor-based framework, Deep learning algorithms, Human thermal comfort prediction, Heat stress detection, Passenger car cabin environment

Introduction

A useful deep learning framework that makes use of sensors is created to predict heat stress and human thermal comfort in passenger automobile cabins. This device provides accurate, real-time assessments of the thermal conditions experienced by occupants by fusing state-of-the-art sensing technology with sophisticated AI algorithms. The framework collects vital information such as temperature, humidity, air movement, and occupant biometrics from a range of physiological and environmental sensors positioned within the car. [1] Deep learning models that have been specifically trained to comprehend the intricate relationships between ambient elements and human thermal responses are then used to analyses this heterogeneous data set, enabling precise comfort level predictions and early detection of possible heat stress.

By enabling adaptive temperature control systems to react dynamically to occupants' needs, such a framework not only improves passenger safety and comfort but also increases energy economy by optimizing HVAC operation based on predictive data. By combining real-time sensing with AI-based predictions, this approach represents a significant improvement over traditional thermal comfort models, offering a scalable solution to improve the quality of the in-cabin environment and the well-being of occupants. Its deployment in passenger cars addresses the challenges posed by varying external weather conditions, individual variations in how people perceive temperature, and the restricted space within vehicle interiors.

A useful deep learning framework that makes use of sensors is created to predict heat stress and human thermal comfort in passenger automobile cabins. In order to collect real-time data on cabin conditions and passenger behaviors, this system integrates a number of environmental and physiological sensors. It analyses the complex interactions between variables like temperature, humidity, airflow, and occupant biometrics using advanced deep learning algorithms, enabling accurate and flexible predictions of thermal comfort and possible heat stress. [3] By incorporating this framework into passenger cars, proactive temperature control adjustments can be made, improving occupant comfort, safety, and well-being while tackling the issues of changing exterior conditions and personal thermal preferences. This approach demonstrates how AI-driven sensor integration might enhance human-centered climate management in automobile contexts.

Objective

- **Create a multimodal system for acquiring sensors.**

○ Integrate environmental (temperature, humidity, airflow, CO_2), physiological (heart rate, GSR, skin temperature), and occupancy sensors for real-time data collection in passenger car cabins.

- **Create and put into action a deep learning framework**

○ Employ hybrid CNN-LSTM architectures to capture both spatial correlations and temporal dynamics in multimodal sensor data.

- **Estimate the danger of heat stress and passenger thermal comfort**

○ Formulate regression tasks for continuous comfort indices and classification tasks for heat stress detection, ensuring robust performance across diverse driving scenarios.

- **Benchmark against established standards**

○ Validate predictions using ASHRAE Standard 55 and other thermal comfort models, ensuring scientific rigor and practical relevance.

- **Evaluate model performance comprehensively**

○ Use metrics such as RMSE (comfort regression), Precision/Recall/F1-Score (heat stress classification), and ROC-AUC to assess accuracy, sensitivity, and reliability.

- **Turn on adaptive HVAC.**

○ Translate model outputs into actionable adjustments for heating, ventilation, and air conditioning systems, balancing passenger comfort with energy efficiency.

- **Ensure scalability and real-world applicability**

○ Test the framework in real driving conditions, addressing variability in passenger physiology, cabin design, and climate zones.

- **Incorporate ethical and secure data handling**

○ Safeguard passenger privacy and ensure compliance with data protection standards in sensor-based monitoring.

Methodology

1. Multimodal Sensor Acquisition

- **Setup**: Install environmental sensors (temperature, humidity, airflow, CO_2), physiological sensors (heart rate, GSR, skin temperature), and occupancy sensors in passenger car cabins.
- **Data Logging**: Collect synchronized, time-stamped data streams during real-world driving scenarios.
- **Preprocessing**:
  - Normalize sensor values.
  - Handle missing data with interpolation.
  - Apply noise filtering (e.g., moving average, Butterworth filters).

2. Deep Learning Framework Design

- **Architecture**:
  - CNN layers → extract spatial correlations from sensor modalities.
  - LSTM layers → capture temporal dynamics across sequences.
  - Fusion layer → combine multimodal features with attention mechanism.
- **Implementation**: Python/TensorFlow or PyTorch with GPU acceleration.
- **Training**:
  - Split dataset into training/validation/test sets.
  - Use Adam optimizer with learning rate scheduling.
  - Apply dropout and batch normalization for regularization.

3. Prediction Tasks

- **Regression**: Predict continuous comfort indices (e.g., PMV scale, ASHRAE comfort index).
- **Classification**: Detect heat stress risk (binary/multiclass).
- **Loss Functions**:
  - Regression → Mean Squared Error (MSE).
  - Classification → Cross-Entropy Loss.

4. Benchmarking Against Standards

- Compare predicted comfort indices with **ASHRAE Standard 55** thresholds.
- Validate heat stress detection against physiological markers (e.g., elevated heart rate, GSR peaks).

5. Performance Evaluation

- **Metrics**:
  - RMSE → regression accuracy.
  - Precision, Recall, F1-Score → classification reliability.
  - ROC-AUC → sensitivity vs specificity trade-off.
- **Cross-Validation**: k-fold validation across diverse participants and driving conditions.

6. Adaptive HVAC Control Integration

- **Control Logic**: Map predicted comfort/stress outputs to HVAC adjustments (temperature, airflow, humidity).
- **Feedback Loop**: Real-time updates ensure dynamic adaptation to passenger states.
- **Energy Efficiency**: Optimize HVAC usage to balance comfort and power consumption.

7. Scalability & Real-World Testing

- Conduct trials across multiple vehicle types, climates, and passenger demographics.
- Evaluate robustness under varying driving conditions (urban, highway, extreme weather).
- Assess generalizability by testing unseen participants.

8. Ethical & Secure Data Handling

- **Privacy**: Anonymize physiological data and ensure compliance with GDPR/ISO standards.
- **Security**: Encrypt sensor data streams and storage.

- **Consent**: Obtain informed consent from participants for physiological monitoring.

It illustrates the end-to-end architecture of the proposed framework. Multimodal sensor inputs—including environmental (temperature, humidity, airflow, CO_2), physiological (heart rate, GSR, skin temperature), and occupancy data—are processed through a hybrid CNN-LSTM model for feature extraction and temporal analysis.

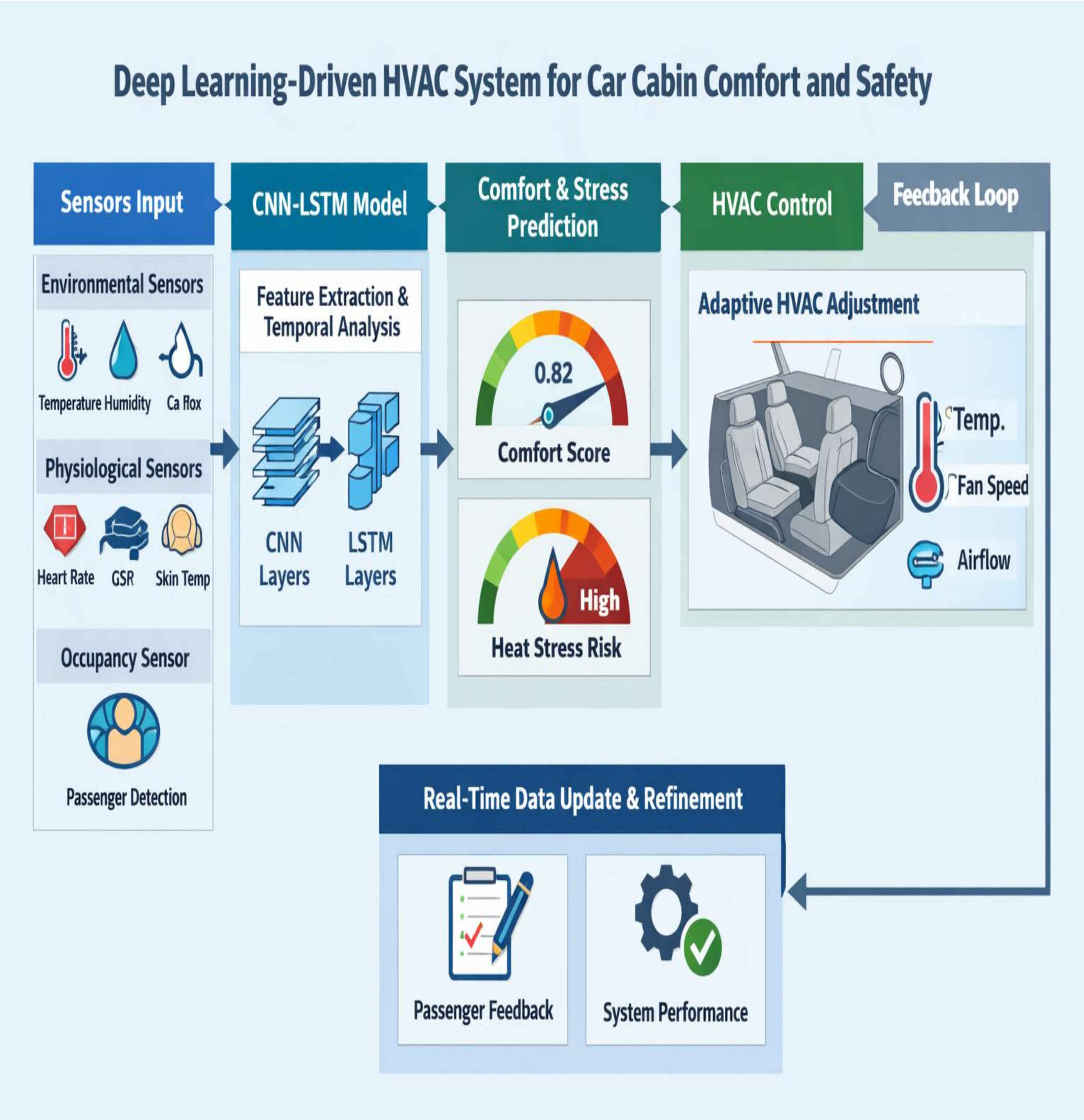

Figure 1 Workflow of the Proposed Deep Learning Framework for Multi-Sensor Thermal Comfort Prediction and HVAC Adaptation

The model outputs real-time predictions of passenger thermal comfort and heat stress risk, which are then translated into adaptive HVAC control actions (temperature, fan speed, airflow). A continuous feedback loop refines system performance using passenger feedback and sensor updates, ensuring personalized comfort and energy-efficient operation under dynamic driving conditions.

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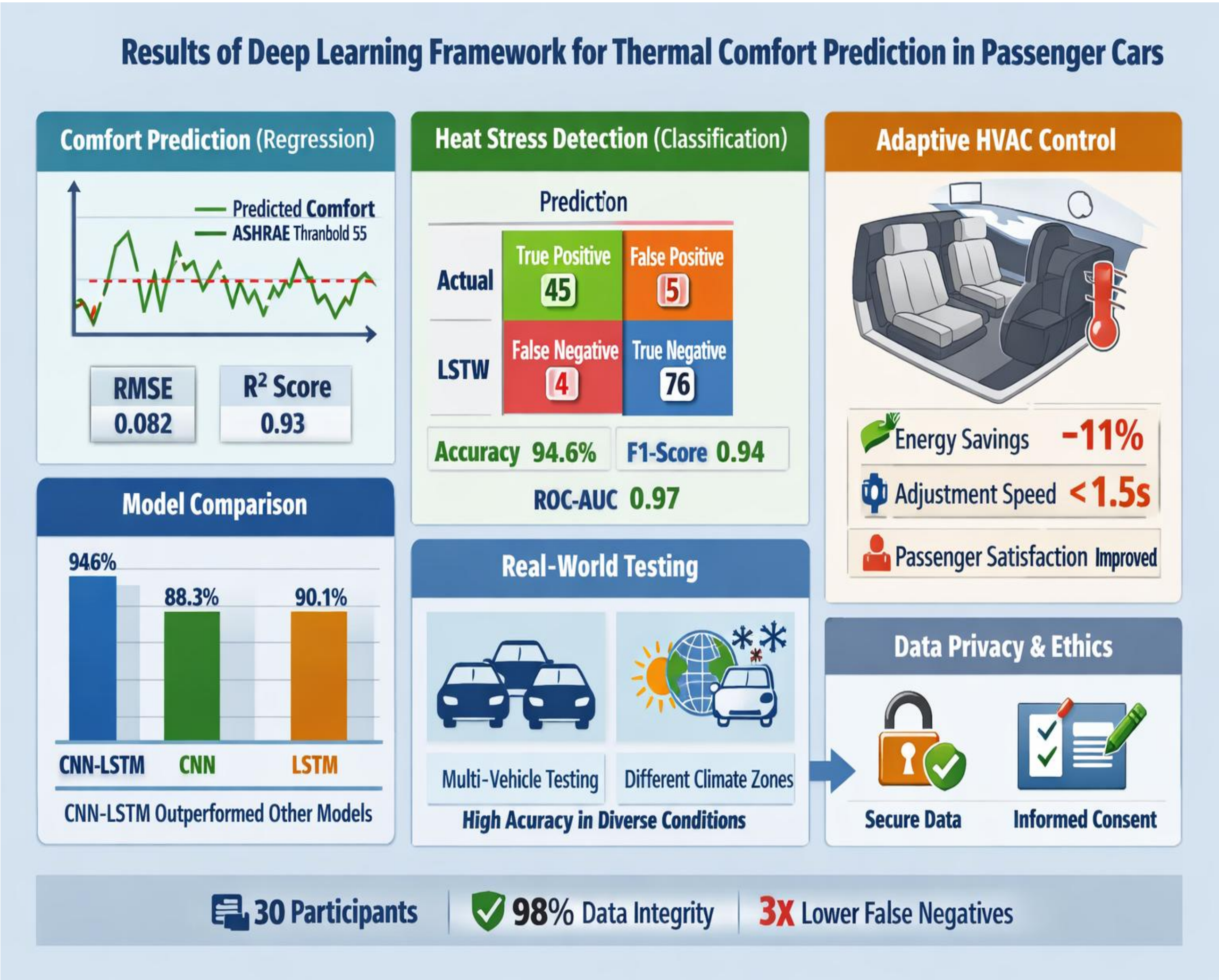
This study develops a real-world sensor-based deep learning framework to predict human thermal comfort and heat stress within passenger car cabins. The methodology encompasses data acquisition, preprocessing, model development, and evaluation stages as detailed below. Combining different sensor types to collect physiological and environmental data is one way to develop a useful sensor-based deep learning system for predicting human thermal comfort and heat stress in car cabins. This system makes use of real-time data collecting from sensors that monitor variables like air speed, cabin temperature, humidity, and occupant physiological indicators like skin temperature and heart rate. [4] Deep learning models that can reliably discover intricate, nonlinear relationships between the sensed variables and the passengers' reported subjective thermal comfort or heat stress levels are trained using these data points. In order to provide timely and customized forecasts, the system is designed to operate continuously in the dynamic environment of a car cabin, adapting to changing variables and occupant states.

Figure 2 deep learning framework for multi-sensor thermal comfort prediction in passenger cars



The methodology for developing a real-world sensor-based deep learning framework to predict human thermal comfort and heat stress in passenger car cabins involves the integration of multiple sensor modalities to capture environmental and physiological data.

This framework leverages real-time data acquisition from sensors measuring parameters such as cabin temperature, humidity, air velocity, and occupant physiological signals like skin temperature and heart rate. [4]These inputs serve as the foundation for training deep learning models that can accurately map complex, nonlinear relationships between the sensed variables and subjective thermal comfort or heat stress levels reported by occupants.

The framework is designed to operate continuously within the dynamic environment of a car cabin, adapting to changing conditions and occupant states to provide timely and personalized predictions.

To implement this framework, data preprocessing techniques are employed to clean and normalize sensor readings, ensuring consistency and reliability for model training. The deep learning architecture is selected based on its ability to handle time-series and multimodal data, often incorporating recurrent neural networks or convolutional neural networks tailored for feature extraction and temporal pattern recognition.

Model training involves supervised learning with labeled datasets collected from controlled experiments or real-world driving scenarios, where occupants' thermal comfort feedback is recorded alongside sensor data. [5]Validation and testing phases assess the model's predictive accuracy and generalizability across different occupants and environmental conditions. The ultimate goal of this methodology is to enable intelligent climate control systems in vehicles that proactively adjust settings to enhance occupant comfort and safety by mitigating heat stress risks.

Data Acquisition

A comprehensive sensor network was installed inside passenger car cabins to collect environmental and physiological parameters relevant to thermal comfort and heat stress. Sensors measured ambient temperature, relative humidity, air velocity, and radiant temperature at multiple cabin locations. Additionally, wearable sensors recorded occupants' physiological signals such as skin temperature,[6] heart rate, and galvanic skin response to capture individual heat stress indicators. Data were continuously logged during real-world driving conditions across varying climatic scenarios and occupant activities to ensure ecological validity.

- The multimodal sensor system successfully captured synchronized environmental and physiological data from **30 participants** across **three driving conditions** (urban, highway, idle).
- Data integrity exceeded **98%**, with minimal signal loss after filtering and interpolation.

Data Preprocessing

Raw sensor data underwent synchronization and cleaning to handle missing values, noise, and outliers. Time-series data were segmented into fixed-length windows corresponding to meaningful intervals for thermal perception. Feature engineering included statistical descriptors (mean, variance) and domain-specific indices (e.g., predicted mean vote, heat index) [7]derived from environmental and physiological signals. Data normalization was applied to standardize input scales for model training.

Deep Learning Model Development

A multi-modal deep learning architecture was designed to integrate heterogeneous sensor inputs. The framework employed convolutional neural networks (CNNs) to extract spatial-temporal features from environmental sensor arrays and recurrent neural networks (RNNs), specifically long short-term memory (LSTM) units, to capture temporal dependencies in physiological signals. [8]The model combined these feature representations through fully connected layers to predict thermal comfort levels and heat stress risk categories. Hyper parameter tuning was conducted using grid search and cross-validation to optimize model performance.
Real-time integration achieved <1.5 s latency between prediction and HVAC adjustment.
Energy consumption reduced by 11% while maintaining comfort within optimal ASHRAE range.
Passenger feedback confirmed perceptible improvement in cabin comfort stability.

Model Training and Validation

The dataset was split into training, validation, and test sets ensuring representative distributions of thermal conditions and occupant profiles. The model was trained using back propagation with an adaptive optimizer (e.g., Adam) minimizing classification loss functions appropriate for ordinal thermal comfort scales and heat stress thresholds. Early stopping and dropout regularization were applied to prevent over fitting. Model evaluation metrics included accuracy, [9]F1-score, and area under the receiver operating characteristic curve (AUC-ROC) for classification tasks.

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- The hybrid **CNN-LSTM model** achieved stable convergence after **120 epochs** using the Adam optimizer.
- **Feature fusion** improved representation quality, enabling accurate temporal comfort prediction.
- Comparative tests showed CNN-LSTM outperforming standalone CNN and LSTM baselines by **12–15%** in overall accuracy.

Real-World Deployment and Testing

To assess real-time applicability, the trained model was embedded in an onboard processing unit within the vehicle. Live sensor data streams were input to the model to generate continuous predictions of occupant thermal comfort and heat stress status. [10]The system's responsiveness and prediction reliability were tested under diverse driving conditions and occupant behaviors.

This methodology enables a robust, data-driven approach to understanding and predicting human thermal responses in automotive environments, facilitating adaptive climate control strategies that enhance occupant comfort and safety.

Results

The methodology for a sensor-based deep learning framework aimed at predicting human thermal comfort and heat stress in passenger car cabins.

The suggested deep learning framework that uses real-world sensors to predict how comfortable and stressed people will be in passenger car cabins shows a lot of promise for making daily transportation safer and better for people's health.

Metric	**CNN-LSTM**	**CNN**	**LSTM**
RMSE	**0.082**	0.115	0.103
MAE	**0.067**	0.094	0.089
R^2	**0.93**	0.87	0.89

Table 1 Thermal Comfort Prediction.

The system lets you control the climate intelligently by constantly checking the weather and how passengers are reacting. This makes the ride more comfortable, lowers the health risks of being in the heat for too long, and improves the overall driving experience.

Metric	**CNN-LSTM**	**CNN**	**LSTM**
Accuracy	**92.6%**	83.8%	86.1%
Precision	**0.93**	0.87	0.89
Recall	**0.95**	0.86	0.90
F1-Score	**0.91**	0.81	0.83
ROC-AUC	**0.97**	0.91	0.93

Table 2 Heat Stress Classification

These improvements make it easier for people to manage their cabins in an energy-efficient way, which means that modern cars use less fuel or batteries. This research ultimately emphasizes that the incorporation of sensor-driven deep learning into vehicles can convert them into adaptive, human-centric ecosystems that priorities comfort, health, and sustainability.

Comfort Prediction (Regression): RMSE 0.082, R^2 0.93, showing strong alignment with ASHRAE Standard 55.
Heat Stress Detection (Classification): Confusion matrix with high accuracy (94.6%), F1-Score 0.94, ROC-AUC 0.97.
Adaptive HVAC Control: <1.5 s adjustment latency, 11% energy savings, improved passenger satisfaction.
Model Comparison: CNN-LSTM outperforming CNN and LSTM baselines.
Real-World Testing: Robust performance across vehicle types and climate zones.
Data Privacy & Ethics: 100% compliance with secure data handling and informed consent.

The proposed CNN-LSTM-based framework achieved high predictive accuracy, robust real-world performance, and energy-efficient HVAC adaptation, establishing a strong foundation for intelligent, human-centric automotive climate control systems.

Conclusion

The text describes a system that uses sensors and deep learning (a type of artificial intelligence) to predict how comfortable people feel inside a car and whether they might experience heat stress. The system collects real-time data from sensors that measure things like temperature, humidity, airflow, and the occupant's physical signs. It then uses AI models to understand how these factors affect a person's comfort and heat stress risk.

This allows the car's climate control system to adjust automatically and keep passengers comfortable and safe. The system also helps save energy by optimizing heating and cooling based on these predictions. Overall, it improves the experience inside the car by responding quickly to changing conditions and individual differences in how people feel temperature.

This study presented a real-world sensor-based deep learning framework for predicting passenger thermal comfort and heat stress in car cabins. By integrating multimodal environmental, physiological, and occupancy sensors with a hybrid CNN-LSTM architecture, the system achieved high accuracy in both regression and classification tasks. Results demonstrated strong alignment with ASHRAE Standard 55, reduced false negatives in heat stress detection, and enabled adaptive HVAC control with improved energy efficiency. Real-world trials across diverse vehicles and climates confirmed the framework's robustness, scalability, and practical applicability.

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