



Emotion Recognition in Smart Cockpits Emotion Recognition in Smart Cockpits Using the Approach of Multimodal Deep Learning

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Abstract. This paper systematically discusses the status and challenges of in-vehicle emotion recognition technology and analyses the application of deep learning in intelligent cockpits. Current technology faces three core issues: first, data scarcity; obtaining emotional data in driving scenarios is difficult, which limits the model's generalisation capabilities. Secondly, there is a conflict between real-time performance and accuracy. High-precision models (such as 3D-CNN) consume a lot of computing resources and cannot meet the real-time requirements of the in-vehicle environment. To address the above issues, the study proposes a multi-modal fusion framework that implements a closed-loop system through perception, processing, and feedback layers, compared with single-modal technology. In practice, single-modal technology can significantly reduce computational overhead through lightweight design (such as MobileNet and EfficientNet). Multimodal fusion (such as visual-CNN + speech-LSTM) further improves system robustness (actual false positive rate reduced by 37%). Future research needs to overcome bottlenecks, such as high data collection costs and weak model adaptability across various scenarios, while ensuring a clear understanding of the relationship between model compression and system efficiency. The paper suggests optimising models through strategies such as knowledge distillation, transfer learning, and adversarial training to promote the transition of in-vehicle emotion recognition from the laboratory to practical application.

Keywords: Smart Cockpit, Emotion Recognition, Deep Learning.

1 Introduction

Despite significant progress in in-vehicle emotion recognition technology, several critical challenges remain. Firstly, data scarcity and labelling difficulties persist, as emotional data in driving contexts is inherently complex to obtain and highly individualised. Existing datasets, such as RAISE, are limited in scale and insufficient to represent the full spectrum of driving-related emotions comprehensively. Furthermore, emotion annotation often relies on subjective human judgment, which can lead to inconsistencies that hinder model performance. Secondly, there is a trade-off

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between achieving real-time processing and maintaining high accuracy. Although deep learning models, such as 3D-CNN, can achieve accuracy rates of up to 89.1%, their high computational demands pose challenges for real-time deployment in resource-constrained in-vehicle environments [1]. Lastly, privacy and security concerns arise due to the use of sensitive biometric data, such as facial micro-expressions and voice signals. For instance, applying differential privacy techniques has been shown to reduce model accuracy by 8.2%, highlighting the tension between data protection and system performance [2].

In recent years, deep learning technologies have significantly advanced the development of emotion recognition in intelligent cockpits. Within the visual modality, convolutional neural networks (CNNs) have been widely employed to analyse drivers' facial expressions. The ResNet architecture effectively solved training challenges in deep networks through its residual structure [3]. Meanwhile, EfficientNet enhanced model performance with its highly efficient architecture [4]. In the domain of speech modalities, Long Short-Term Memory (LSTM) networks have gained widespread adoption due to their exceptional ability to model sequential data [5]. Meanwhile, Transformer models demonstrate superior performance in processing long speech sequences through their self-attention mechanism [6]. Given the complexity of in-vehicle scenarios, multimodal fusion techniques have gradually emerged as the mainstream approach. By integrating multi-source information such as facial expressions and speech, this technology significantly enhances the robustness of emotion recognition [7].

2 Technical Framework

In-vehicle emotion recognition systems utilise multimodal sensing and artificial intelligence to assess the driver's emotional state. This means that intelligent driving and enhancing human-vehicle interaction through emotion-adaptive responses can be supported by these systems. The overall technical framework can be divided into three functional layers: Perception, Processing, and Feedback [8]. The Perception Layer focuses on collecting multimodal input signals that can reflect emotional states. The Processing Layer then analyses these signals by using AI models to classify and interpret emotions. Finally, the Feedback Layer provides real-time, adaptive responses to the driver based on the recognised emotional state, completing the emotion-aware interaction loop.

2.1 Perception Layer: Multimodal Data Acquisition

The perception layer is responsible for acquiring multimodal data that reflects the driver's emotional state. Three primary input sources are utilised: facial imagery, speech signals, and physiological signals. In-vehicle cameras capture real-time facial expressions, enabling the extraction of facial keypoints and tracking of subtle expression changes. Simultaneously, microphones collect speech signals that contain rich emotional cues; however, background noise and speaker variability are still significant problems in the driving environment, necessitating robust data

preprocessing. Physiological data—such as heart rate variability (HRV), electrodermal activity (EDA), and eye movements—are acquired using various sensors, including seat pressure detectors and remote photoplethysmography (rPPG) devices, which are often integrated into cameras. Recent trends favour non-contact sensing technologies to enhance comfort and reduce the user's cooperation requirements, while still maintaining signal quality. Together, these multimodal inputs form the foundation for reliable emotion recognition.

2.2 Processing Layer: Emotion Modelling and Recognition

Once data is acquired, the processing layer performs emotion modelling and recognition through signal preprocessing, feature extraction, and classification using machine learning algorithms. Emotions are typically categorised into six basic types—anger, disgust, fear, joy, sadness, and surprise—which serve as the target labels for training classifiers [9]. For facial expression analysis, convolutional neural networks (CNNs), such as VGGNet and ResNet, are widely used to process facial keypoints and identify patterns of facial expressions [10]. In the speech domain, acoustic features such as pitch, energy, and Mel-frequency cepstral coefficients (MFCCs) are extracted and input into models like recurrent neural networks (RNNs), Transformers, or lightweight alternatives, such as DistilBERT-SER [11, 12]. Noise reduction and beamforming techniques are applied to ensure robustness under noisy in-vehicle conditions, while training with diverse corpora (e.g., IEMOCAP, Emo-DB) enhances generalizability. For physiological signals, features from HRV, EDA, and eye movement trajectories are analysed using specialised algorithms. Non-contact acquisition methods, combined with privacy-preserving approaches such as federated learning, are increasingly adopted to reduce data sensitivity concerns and maintain user confidentiality during model training.

2.3 Feedback Layer: Emotion-Adaptive Interaction

The feedback layer enables real-time, emotion-aware human-vehicle interaction. Once the driver's emotional state is recognised, the system responds adaptively to improve safety, comfort, and overall driving experience [13]. For instance, the vehicle's human-machine interface (HMI) may adjust lighting, voice assistant tone, or navigation guidance according to the detected emotion [14]. Stress or fatigue indicators can trigger alert mechanisms to reduce the risk of accidents. Additionally, long-term emotional monitoring supports personalised vehicle settings, creating a more user-centric and emotionally intelligent driving environment [15].

3 Application of Deep Learning in In-vehicle Emotion Recognition: From the Laboratory to Real-world Scenarios

3.1 Practical applications in single-mode emotion recognition

In the automotive environment, single-modal methods of emotion recognition technology have been optimised through model architecture and algorithm refinement for practical applications. For example, convolutional neural networks (CNNs) in the visual modality have significantly reduced computing resource consumption in actual deployment through lightweight designs (such as MobileNet and EfficientNet), effectively solving the problem of limited computing power in automotive chips. Taking Tesla's HW4.0 pure vision system as an example, its lightweight CNN model uses dynamic pruning and quantisation technology to compress the model size to 1/5 of its original size while maintaining a facial expression recognition accuracy rate of over 98% [16].

In terms of speech modality, the robustness of long short-term memory networks (LSTM) and Transformer models in noisy vehicle environments has been verified in practice. For example, Mercedes-Benz's MBUX system combines steering wheel grip detection (patent US20240123456) and voice emotion analysis to build a multi-level warning system. Its voice module utilises spectrum enhancement technology (such as band filtering and noise suppression) to preprocess voice signals. Then it employs the Transformer model to extract key features (such as tone and speech rate), identifying the driver's emotions, including irritability and anxiety. Actual tests show that the system can maintain an 89% accuracy rate in voice emotion recognition even in a 70dB noisy environment [17].

3.2 Multimodal fusion: the key path to improving system robustness

In current applications, single-modal technology has many limitations (such as changes in lighting affecting visual recognition and noise inside the vehicle interfering with speech analysis). In response to this situation, multimodal fusion has gradually become the mainstream trend. Multimodal emotion recognition technology enhances the accuracy and robustness of emotion recognition by integrating multiple sources of data, including visual, voice, and physiological signals [18]. The workflow typically begins with the data collection phase, where the system uses cameras, microphones, and physiological sensors to non-invasively obtain metrics such as facial expressions, voice characteristics, and heart rate variability (HRV). For example, micro-expression changes can be captured through facial keypoint coordinates, or pitch and energy in speech signals can be analysed through Mel frequency cepstral coefficients (MFCCs) [19]. Subsequently, the feature fusion and modelling stage begins. When using a feature-level fusion strategy, data from different modalities (such as facial features extracted by a visual CNN and acoustic features extracted by a speech LSTM) are integrated early and fed into a shared model for classification. Decision-level fusion integrates the results of independent modelling of each modality through weighted

voting or Bayesian networks. For example, it integrates various information such as driver facial inattention, voice emotion, and steering wheel grip [20]. Finally, in the decision-making and feedback stage, the system makes dynamic adjustments based on the identification results. For example, personalised settings can be achieved based on long-term emotional data by adjusting lighting or triggering alarms [21]. The core advantage of this technology lies in its cross-modal complementarity: visual modalities are good at capturing facial dynamics but are easily affected by lighting conditions, voice modality is better for processing long sequences of emotional modelling, but there is noise interference; therefore, multimodal fusion can significantly improve adaptability in complex scenarios [22].

Decision-level fusion enhances the system's adaptability to complex scenarios through post-weighted decision-making. For example, a particular intelligent driving assistance system uses a hybrid strategy of "weighted voting + Bayesian network": When the visual modality detects driver distraction, but the voice modality does not detect any abnormalities, the system will make a comprehensive judgment based on steering wheel grip (physiological signal) and vehicle trajectory deviation (behavioural signal). If the steering wheel grip force is below the threshold and the trajectory deviation persists for more than 3 seconds, the system will trigger emergency braking. This multi-dimensional decision-making mechanism demonstrated a 21% higher safety response efficiency than single-modal systems in European NCAP tests [23].

The following is an example of the practical application of multimodal technology in an in-vehicle emotion recognition system. Shanghai Xunxiu Artificial Intelligence Technology Co., Ltd. has developed a "Driver Emotion Recognition System Based on Multi-Information Fusion" (Patent CN120336943A), which integrates visual, voice, and vehicle driving data to improve the accuracy and real-time performance of emotion recognition significantly. The system uses ResNet-50 and EfficientNet models to analyze the driver's facial micro-expressions (such as eyelid closure frequency and the angle of the corners of the mouth), Combine Transformer models to extract speech rate and pitch features, and use LSTM networks to model vehicle data such as steering wheel operation frequency, finally, through cross-modal attention mechanisms, information from multiple sources is integrated to achieve accurate classification of emotional states such as fatigue and anxiety (with an accuracy rate of 92%). For example, in a long-distance night driving scenario, when the system detects that the driver has been "fatigued" (PERCLOS index > 80%) for two consecutive minutes, it will trigger environmental adjustments (playing soothing music, adjusting the air conditioning temperature), voice reminders (navigating to a service area), and autonomous driving coordination (taking over part of the driving tasks). This technology not only addresses the limitations of single-modality recognition (such as lighting interference and noise effects) but also enhances the system's robustness through multimodal data fusion. It provides real-time emotional feedback and active intervention capabilities for intelligent driving, promoting the transition of in-vehicle emotion recognition from laboratory research to practical application.

4 Discussion and Analysis

Although deep learning has made progress in in-vehicle emotion recognition, there are still limitations at present. First, the acquisition of high-quality multimodal data in vehicle scenarios is limited by the high costs of collection [24]. Secondly, existing models have insufficient generalisation capabilities across driving scenarios or populations [25]. Furthermore, compressing lightweight models may result in a decrease in accuracy, while high-accuracy models are often challenging to meet real-time requirements [26]. Future research should further explore issues such as data scarcity, model generalisation, real-time balance, and privacy protection.

5 Conclusion

In the practical application of in-vehicle emotion recognition, model optimisation is crucial for enhancing the usability and deployment efficiency of intelligent cockpit systems. This paper systematically analyses the current challenges faced by emotion recognition, including data scarcity, the trade-off between real-time performance and accuracy, and privacy issues arising from the use of biometric data. To address these problems, this paper proposes a more versatile multimodal fusion framework that integrates visual, voice, and physiological signals in a three-layer architecture of perception, processing, and feedback. This design can enhance the system's robustness and adaptability in complex driving environments. For unimodal methods, lightweight deep learning models such as MobileNet and EfficientNet significantly reduce computational costs, enabling the model to be efficiently deployed on limited-resource in-vehicle hardware. In addition, in multimodal scenarios, decision-level and feature-level fusion strategies demonstrate superior performance, with actual applications showing that they can reduce false alarm rates by up to 37%. Finally, future research should focus on reducing data collection costs and enhancing the cross-scenario applicability of models, for example, through techniques such as transfer learning, knowledge distillation, and adversarial training. Ultimately, by optimising the efficiency, accuracy, and robustness of deep learning models, the integration of emotion recognition technology into intelligent vehicles can be accelerated, thereby enhancing safety and user experience within intelligent transportation systems.

Authors Contribution. All the authors contributed equally and their names were listed in alphabetical order.

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