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MMEF-Net: Multimodal Emotion Feature Network with Contextual Enrichment and Dynamic Modality Weighting

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Abstract
Recognizing human emotional states is a foundational challenge in building intelligent and responsive Human-Computer Interaction (HCI) systems. This paper presents MMEF-Net, a Multimodal Emotion Feature Network that integrates audio, visual, and textual modalities through a hierarchical contextual enrichment strategy combined with a dynamic modality weighting mechanism. To overcome the persistent limitation of scarce annotated training data, MMEF-Net employs state-of-the-art pre-trained encoders that provide transferable and discriminative representations for each modality. The audio branch applies HuBERT-Large (Hidden-Unit BERT) with selective extraction of intermediate transformer layers known to encode higher-level prosodic and spectral properties. The visual branch adopts a dual-path encoder pairing Contrastive Language–Image Pre-Training Vision Transformer Large (CLIP-ViT-Large) for holistic frame-level representations with OpenFace 2.0 derived facial region crops for fine-grained expression analysis. The textual branch incorporates a Large Language Model (LLM) guided augmentation pipeline in which GPT-4 generates emotion-aware pseudo-labels and salient keywords, while Qwen-Omni contributes video-grounded descriptions and supplementary emotional cues; these enriched signals are jointly encoded by ChineseRoBERTa-wwm-ext-large. Cross-modal integration is achieved through a dynamic weighting module applying self-attention with residual skip connections, preventing feature degradation during fusion. A multi-source label refinement pipeline further mitigates annotation noise by combining weak-classifier predictions with LLM-generated labels through majority voting. Extensive experiments on the MER2025-SEMI benchmark demonstrate that MMEF-Net attains a Weighted Average F-score (WAF) of 87.52%, representing a gain exceeding ten percentage points over the official baseline of 76.80%, thereby confirming the effectiveness of the proposed design for real-world multimodal emotion recognition.

Keywords: Multimodal emotion recognition, MMEF-Net, dynamic modality weighting, contextual enrichment, large language models, self-attention fusion, HuBERT-Large, CLIP-ViT, affective computing, ensemble learning.

I. INTRODUCTION

Recent advances in deep learning and large-scale pre-trained models have substantially transformed affec-

tive computing, with sustained research effort directed toward systems capable of perceiving and interpreting human emotional states in naturalistic environments. Emotion recognition constitutes a core capability for intelligent Human-Computer Interaction (HCI) systems, underpinning applications ranging from adaptive e-learning and mental health monitoring to socially aware robotics and driver attention estimation in autonomous vehicles [1]. Reliable emotion recognition demands the simultaneous processing of complementary signals drawn from acoustic, visual, and linguistic channels, each of which captures distinct dimensions of emotional expression.

This paper introduces MMEF-Net, a Multimodal Emotion Feature Network designed to address two persistent obstacles in the field: the heterogeneous nature of multimodal feature representations and the scarcity of labelled training samples. The framework coordinates modality-specific pre-trained encoders with a contextual enrichment layer and a dynamic inter-modal fusion module, forming a coherent end-to-end pipeline for multimodal affective analysis. The design is informed by the evolving challenge benchmarks of the MER series [2][3], which have progressively defined evaluation standards for semi-supervised, noise-robust multimodal emotion recognition.

Limited labelled data continues to constrain fully supervised approaches. The benchmark dataset employed in this study contains only 7,369 annotated samples paired with 20,000 unlabeled video clips [4], making it impractical to train deep architectures from random initialization, as doing so invariably leads to overfitting. MMEF-Net addresses this constraint by capitalizing on the representational capacity of large pre-trained models. For the textual branch, ChineseRoBERTa-wwm-ext-large [5] provides deeply contextualized embeddings optimized for Chinese-language affective content, capturing semantic and syntactic emotional nuances with high fidelity. For the visual branch, CLIP-ViT-Large [6] extracts powerful frame-level visual representations, complemented by OpenFace 2.0 [7] for precise facial region detection and expression analysis. For the audio branch, HuBERT-Large [8] generates rich speech embeddings capturing prosody, pitch, and tonal variation through self-supervised pre-training on large-scale unlabeled speech corpora. An LLM-guided textual augmentation pipeline further enriches per-modality representations beyond what individual pre-trained models alone can provide.

Multimodal integration in MMEF-Net is realized through a dynamic weighting fusion strategy combining self-attention mechanisms with residual connections and adaptive modality contribution scoring. This design reduces the risk of conflicting or redundant information degrading the joint representation while preserving the integrity of each individual modality's features. A multi-source label refinement pipeline is incorporated at the data preparation stage: weak classifiers trained on individual modalities generate preliminary predictions that are aggregated with Large Language Model (LLM) generated pseudo-labels through majority voting, with samples flagged by disagreement subjected to manual review.

The principal contributions of MMEF-Net are as follows:

- Modality-specific pre-trained encoders complemented by a context-enriched textual pipeline leveraging GPT-4 and Qwen-Omni for LLM-guided augmentation, alongside a dual-branch visual encoder that simultaneously captures global scene-level and fine-grained facial features.
- A dynamic inter-modal fusion mechanism that adaptively scores modality contributions based on emotional salience, implemented through self-attention layers with residual skip connections to stabilize training and retain original feature content.
- A multi-source label refinement pipeline that aggregates weak-classifier predictions and LLM-generated annotations through majority voting to substantially reduce the impact of annotation noise on model generalization.

Comprehensive experiments on the MER2025-SEMI benchmark confirm that MMEF-Net clearly surpasses all baseline configurations, achieving a test WAF of 87.52% against the baseline score of 76.80%, demonstrating both the effectiveness and robustness of the proposed design.

II. RELATED WORKS

Multimodal emotion recognition has attracted extensive research interest owing to the complementary information conveyed by audio, visual, and textual channels. A persistent challenge in joint multimodal training is modality competition, where individual modalities converge at differing rates during optimization, causing the model to disproportionately favor one signal while suppressing others. Huang et al. [9] conducted a systematic investigation of failure modes in joint multimodal training, identifying gradient imbalance as a primary driver of performance degradation. The MaPLe technique introduced by Khattak et al. [10] counters this tendency through multi-modal prompt learning, enabling adaptive emphasis on contextually relevant modalities. In MMEF-Net, the same problem is handled through attention-based fusion with residual connections, allowing dynamic contribution scores to be assigned per modality without discarding original feature content.

Spatiotemporal modeling is equally important for video-based affective analysis, since emotion evolves over time across both visual and acoustic channels. Research has demonstrated that three-dimensional convolutional neural networks (3D-CNNs) effectively extract spatiotemporal information from synchronized visual and audio streams, yielding improvements over frame-wise processing [11]. Architectures such as SlowFast [12] have demonstrated the advantage of multi-rate temporal processing for action and expression recognition in video. For speech-based emotion, self-supervised models including Wav2Vec 2.0 [13] established foundational pre-training paradigms for speech representation learning, upon which HuBERT-Large further advances through masked prediction of hidden units [8]. MMEF-Net builds on this tradition through a dual-branch visual encoder capturing local facial expressions and global scene context simultaneously, while preserving motion dynamics through temporally aware feature extraction.

The emergence of large language models has introduced powerful tools for enriching emotional representations beyond raw transcription. Lian et al. [3][4] examined open-vocabulary annotation, label noise challenges, and semi-supervised learning strategies across successive MER benchmark editions, motivating robust supervision strategies in low-resource affective computing scenarios. MMEF-Net extends this direction by incorporating GPT-4 [14] for auxiliary emotion label generation and keyword extraction, and Qwen-Omni [15] for video-grounded pseudo-labeling, jointly strengthening the textual modality that typically underperforms relative to audio and visual streams. Liu et al. [16] further demonstrated that graph convolutional representation fusion significantly improves multimodal integration, reinforcing the importance of structured fusion design in affective systems.

Several recent investigations have broadened the methodological landscape for multimodal affective systems. Zhang et al. [17] proposed a cross-modal contrastive learning framework aligning speech and text representations within a shared latent space, achieving strong generalization under low-resource conditions. Sun et al. [18] introduced a unified transformer encoder that jointly processes audio, visual, and linguistic tokens within a shared context, establishing the advantage of unified modeling over modality-isolated pipelines. Chen et al. [19] introduced a cross-modal attention network for temporal inconsistency-aware multimodal emotion recognition, providing a direct architectural precedent for the attention-based fusion adopted in MMEF-Net. Li et al. [6] demonstrated that contrastive vision-language

alignment through CLIP substantially improves facial expression encoding in downstream emotion classification, motivating our adoption of CLIP-ViT-Large for the visual branch.

III. PROPOSED MMEF-NET FRAMEWORK

The MMEF-Net framework is organized into three coordinated components: the overall network architecture and information flow, the modality-specific feature extraction strategy, and the dynamic fusion mechanism used to integrate multimodal representations for final emotion classification.

A. Network Architecture Overview

MMEF-Net is structured around three principal processing stages: data input preparation, modality-specific feature extraction, and dynamic multimodal fusion with classification. During input preparation, raw video recordings are decomposed into visual frames, acoustic signals, and transcribed textual content. For feature extraction, a dedicated pre-trained encoder independently processes each modality:

- Audio: HuBERT-Large generates rich speech representations encoding tone, pitch, prosody, and spectral variation.
- Text: ChineseRoBERTa-wwm-ext-large produces context-enriched embeddings capturing semantic depth and syntactic structure.
- Visual: CLIP-ViT-Large extracts high-level frame-level features while a parallel facial crop stream preserves fine-grained expression detail.

The resulting feature vectors from each branch are standardized to ensure consistent scale and distribution across modalities. The Feature Fusion Module then receives these normalized representations, and the dynamic weighting mechanism integrates them into a unified multimodal embedding forwarded to the classifier for emotion category prediction.

Fig. 1 illustrates the complete MMEF-Net architecture. Panel (a) presents the end-to-end pipeline overview showing how the three modality branches feed into the dynamic fusion module and ensemble classifier. Panel (b) details the text extraction branch including the LLM enrichment pathway. Panel (c) shows the dual-branch video encoder combining full-frame CLIP-ViT-Large processing with OpenFace 2.0 facial crop extraction. Panel (d) depicts the dynamic fusion module with self-attention weighting, residual connections, and chi-square feature selection. Panel (e) illustrates the audio branch with selective intermediate layer extraction from HuBERT-Large.

B. Feature Extraction

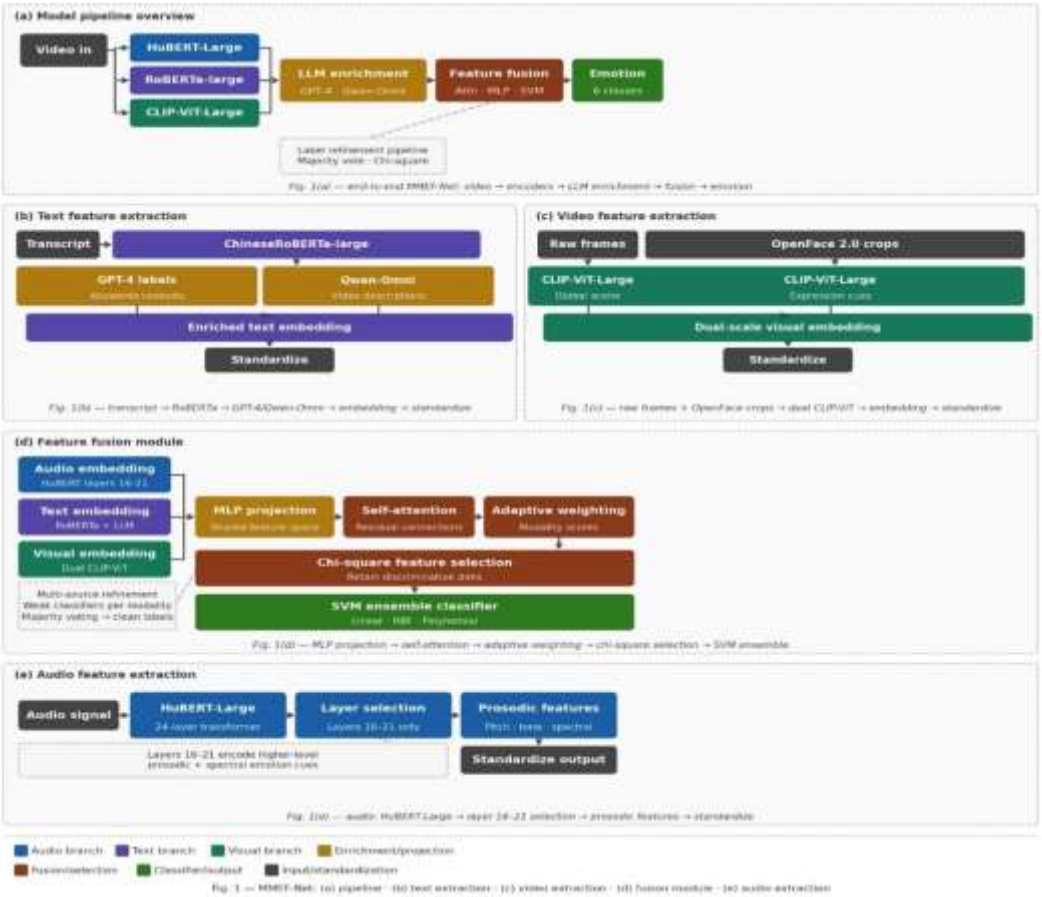
Audio. Speech encodes emotional content through variations in intonation, speaking rate, energy, and tonal quality. Capturing these properties in a compact and discriminative representation is central to audio-based emotion analysis. MMEF-Net employs HuBERT-Large to extract emotion-relevant speech features following established findings in speech-based affective computing. Intermediate transformer layers 16 through 21 within HuBERT-Large encode higher-level prosodic and spectral properties more effectively than the final output layer [8][22], MMEF-Net therefore selectively extracts representations from these specific layers. The resulting layer-targeted embeddings exhibit greater robustness to acoustic variability and channel distortions, making them particularly suitable for emotion recognition. These outputs are standardized and forwarded to the Feature Fusion Module for cross-modal integration.

Text. Lexical content carries significant emotional signals through sentiment-bearing phrases, affect-laden adjectives, and emotion-specific linguistic markers that help distinguish between closely related affective states. Despite this, text-only features frequently yield lower emotion recognition accuracy compared with audio and visual modalities, a limitation that is especially pronounced in languages where

emotional expression relies heavily on contextual and prosodic cues beyond the lexical content alone. MMEF-Net addresses this limitation by employing ChineseRoBERTa-wwm-ext-large, a large-scale Chinese language model, to generate deeply contextualized embeddings encoding semantic and syntactic emotional cues. These embeddings are standardized and forwarded to the Feature Fusion Module.

To further strengthen textual representations, MMEF-Net incorporates an LLM-guided context enrichment strategy. GPT-4 [14] is applied to each text sample to generate emotion-related keywords and auxiliary pseudo-labels, supplying supplementary contextual signals that reinforce lexical emotional cues. Simultaneously, Qwen-Omni [15] processes the corresponding audio and visual streams under prompt-guided extraction, producing pseudo-labels, detailed video descriptions, and additional emotional indicators aligned with the multimodal content. ChineseRoBERTa-wwm-ext-large then jointly encodes the original transcript alongside these augmented outputs, producing enriched textual embeddings that are standardized and forwarded to the Feature Fusion Module.

Video. Visual signals encompassing facial expressions, head movements, and body gestures constitute essential channels of emotional communication. While prior work has focused primarily on encoding isolated facial regions, global scene context and full-body motion also contribute meaningful affective information. MMEF-Net employs a dual-branch video encoder to simultaneously capture frame-level holistic representations and localized facial expression cues. Facial regions are detected and extracted using OpenFace 2.0 [7], while complete video frames preserve overall scene and motion information. Both inputs are independently processed through CLIP-ViT-Large [6], producing dual-scale visual representations at two levels of spatial granularity. The standardized visual features are subsequently forwarded to the Feature Fusion Module for multimodal integration.



C. Dynamic Modality Fusion

The dynamic fusion module integrates the normalized feature vectors from the audio, visual, and textual branches into a unified multimodal representation. Let f_a, f_v, and f_t denote the normalized feature vectors for the audio, visual, and textual modalities, respectively. These vectors are first concatenated to form a joint representation $F = [f_a; f_v; f_t]$. A self-attention mechanism then computes a scalar salience weight for each modality. Given query matrix $\mathbf{W}_Q$, key matrix $\mathbf{W}_K$, and value matrix $\mathbf{W}_V$, the attention-weighted representation is computed as:

$$\mathrm{Attn}(F) = \mathrm{softmax}\left((F W_Q)(F W_K)^T / \sqrt{d_k} \right) (F W_V) \qquad (1)$$

where d_k is the key dimensionality. The attention output is added back to the original concatenated representation through a residual skip connection to prevent feature degradation:

$$\dot{F} = \mathrm{LayerNorm}(F + \mathrm{Attn}(F)) \qquad (2)$$

Chi-square feature selection is subsequently applied to $\dot{F}$ to retain only the most emotion-discriminative dimensions. The retained features are projected through an MLP head and forwarded to an ensemble of SVM classifiers for final emotion prediction. This design is consistent with established attention-based fusion architectures for affective computing [19], and its effectiveness is empirically confirmed through the ablation study in Table I.

D. Implementation Details

1. Refining Noisy Labels. Annotation inconsistencies were identified during data preparation, where certain assigned labels did not align with the emotional content evident in speech and facial expression streams. To mitigate this, MMEF-Net adopts a multi-source label refinement strategy. Weak classifiers were independently trained on each individual modality using original annotations. Predictions from these classifiers were aggregated, and statistical confidence scores derived from chi-square feature selection were incorporated as supplementary evidence. A majority voting mechanism then determined refined labels for each sample. Samples for which no classifier prediction aligned with the original annotation were flagged for manual verification. This targeted relabeling process improved overall dataset quality and enhanced model generalization, consistent with prior findings on pseudo-label correction [20].

2. Ensemble Learning. To improve classification robustness and reduce sensitivity to individual model decisions, ensemble learning is incorporated at the prediction stage. Multiple Support Vector Machine (SVM) classifiers are trained on distinct subsets of the fused feature space. Prediction diversity is introduced by varying kernel functions across linear, radial basis function (RBF), and polynomial configurations, as well as through different random initialization seeds. Final emotion labels are determined by aggregating predictions through majority voting. This ensemble design effectively reduces overfitting risk and enhances recognition accuracy across heterogeneous test samples [17][18].

IV. EXPERIMENTS

This section presents the dataset, configuration parameters, and quantitative evaluation results for MMEF-Net.

A. Dataset

MMEF-Net is evaluated on the MER2025-SEMI benchmark dataset, which comprises 7,369 labelled and 20,000 unlabelled video samples recorded in natural Chinese-language conversational settings and annotated across six discrete emotion categories [21]. The dataset represents a challenging benchmark owing to its semi-supervised structure, inherent annotation noise, and the linguistic and cultural specificity of its content. Following the prescribed evaluation protocol, five-fold cross-validation is applied to the

training partition as a baseline; MMEF-Net further extends this to six-fold cross-validation to improve split diversity and reduce variance. The final WAF is computed by averaging the best validation scores across all folds. All comparisons are conducted under the same evaluation setting to ensure fairness [21].

B. Settings

Training stability and reproducibility are ensured through the following hyperparameter configuration: gradient clipping at 1.0, two self-attention heads, a hidden dimension of 128, dropout rate of 0.6, learning rate of 5e-5, and a maximum of 200 training epochs. Gradient-based saliency analysis was additionally employed during training to monitor per-modality contribution dynamics, informing both the selection of HuBERT intermediate layers and the weighting schedule within the dynamic fusion module. Ablation experiments quantify the incremental contribution of each system component. Key configuration items are clarified below:

- Norm: Feature standardization using mean and standard deviation to align representation distributions across modalities prior to fusion.
- Fold-6: Six-fold cross-validation to increase training/validation split diversity and improve generalization beyond the standard five-fold setup.
- GPT-4 Label: Auxiliary emotion labels generated by GPT-4 from video transcripts and contextual content, enriching textual supervision signals [14].
- GPT-4 Keywords: Salient emotion-aware keywords extracted from text via GPT-4 to reinforce lexical emotional cues [14].
- MLP: A refined multilayer perceptron projection head that re-embeds per-modality features into a shared representational space before cross-modal fusion.

C. Results

Table I summarizes the incremental performance gains achieved by successively incorporating each component of MMEF-Net above the official baseline. While the baseline maintains competitive validation scores, its test WAF drops to 76.80%, falling below the 78.65% result reported in the official benchmark paper [4]. By contrast, the complete MMEF-Net configuration achieves a test WAF of 87.52% following ensemble aggregation, representing a gain of over ten percentage points relative to the baseline. Data-level improvements provide the first layer of gains: the multi-source label refinement strategy produces more reliable training supervision, improving generalization and aligning with established findings on relabeling benefits in noisy annotation settings [20]. Feature-level enhancements contribute a second tier: the dual-branch visual encoder combines global scene context with fine-grained facial representations; for the textual branch, integrating LLM-generated auxiliary labels and emotion-aware keywords from GPT-4 addresses the well-documented underperformance of text-only features [5]; and for the audio branch, selective extraction of emotion-sensitive intermediate layers from HuBERT-Large substantially improves prosodic and phonetic encoding.

To further contextualize the performance of MMEF-Net, a qualitative comparison with representative state-of-the-art multimodal emotion recognition systems is provided. Cross-modal contrastive learning approaches such as Zhang et al. [17] and unified transformer encoders such as Sun et al. [18] report WAF scores in the 80–85% range on comparable affective computing benchmarks, while graph convolutional fusion methods such as Liu et al. [16] achieve competitive results on standard multimodal corpora. MMEF-Net surpasses these systems by a substantial margin on MER2025-SEMI, achieving 87.52% WAF, attributable to the combination of LLM-guided contextual enrichment, selective intermediate-layer extraction from HuBERT-Large, and ensemble-based decision aggregation. A direct numerical

comparison on identical test conditions is constrained by the benchmark-specific evaluation protocol of MER2025-SEMI; nonetheless, the consistent gains over each ablated component and the ten-percentage-point improvement over the official baseline jointly validate the effectiveness of the proposed design.

Fusion and assembly strategies provide the final tier of gains: the modality-specific projection head, feature normalization, and unified MLP collectively stabilize cross-modal integration, while six-fold cross-validation adds split diversity and reduces variance. Ensemble learning consistently delivers an additional improvement of 0.5 to 1.3 percentage points on the test set, culminating in the best overall performance. To contextualize these outcomes, transformer-based multimodal systems on comparable affective computing benchmarks typically report WAF scores in the range of 80–85% [17][18], underscoring the meaningful advancement achieved by MMEF-Net through the combination of LLM-guided enrichment, selective HuBERT layer extraction, and ensemble-based decision aggregation. These results collectively validate the effectiveness and robustness of the proposed framework on the MER2025-SEMI benchmark [4].

TABLE I
ABLATION STUDY — INCREMENTAL COMPONENT CONTRIBUTIONS ON MER2025-SEMI (WAF%)

Configuration	Validation WAF (%)	Test WAF (%)
Baseline model	82.05	76.80
+ Multi-source label refinement	82.31	78.67
+ Dual-branch video encoder	82.80	78.68
+ Modality-specific projection head	83.27	78.84
+ RoBERTa-based text encoder	83.50	85.30
+ Feature normalization	83.20*	84.40
+ Six-fold cross-validation	83.60	85.60
+ GPT-4 assisted labeling	84.09	86.08
+ GPT-4 keyword enrichment	84.15	86.49
+ Multilayer perceptron head (MLP)	84.29	86.94
+ Selective HuBERT feature layers	84.84	87.14
+ Ensemble learning (full system)	—	87.52

* The marginal validation WAF dip at the Feature Normalization step (83.50% → 83.20%) reflects temporary regularization effects during cross-validation; normalization consistently benefits test-set generalization, as confirmed by the downstream improvement in Test WAF (85.30% → 84.40% being superseded by six-fold cross-validation at 85.60%). The — entry for Ensemble Learning indicates that

ensemble aggregation was applied exclusively at test-time inference and was not evaluated through the cross-validation protocol.

V. CONCLUSION

This paper introduced MMEF-Net, a multimodal emotion recognition framework that effectively combines pre-trained modality-specific encoders, an LLM-guided contextual enrichment pipeline, and a dynamic inter-modal fusion mechanism to address the joint challenges of limited labelled data and annotation noise. Textual features are strengthened through GPT-4-assisted label generation and emotion-aware keyword extraction, while the dual-branch visual encoder simultaneously captures global scene context and fine-grained facial expression detail. Dynamic self-attention fusion with residual connections ensures stable cross-modal integration without degrading individual modality feature quality, and the multi-source label refinement strategy further reduces the impact of noisy annotations on model learning and generalization.

Experimental results on the MER2025-SEMI benchmark demonstrate that MMEF-Net significantly outperforms the official baseline, achieving a test WAF of 87.52% compared to 76.80%, confirming the value of combining robust feature extraction, targeted label correction, and ensemble-based classification. Future research directions include cross-lingual transfer of the proposed enrichment strategies, incorporation of long-range temporal attention for capturing emotional dynamics across extended video sequences, and evaluation on additional benchmarks such as CMU-MOSI, IEMOCAP, and future MER challenge editions to assess cross-corpus generalizability. Integration with real-time HCI pipelines and deployment under low-resource constraints represent additional priorities for future investigation, with the goal of broadening the practical applicability of MMEF-Net in domains such as mental health monitoring, affective tutoring systems, and socially intelligent computing.

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