Effective Context Modeling Framework for Emotion Recognition in Conversations

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deeper understanding of the emotions conveyed by speakers in each utterance within a conversation. Recently, Graph Neural Networks (GNNs) have demonstrated their strengths in capturing data relationships, particularly in contextual information modeling and multimodal fusion. However, existing methods often struggle to fully capture the complex interactions between multiple modalities and conversational context, limiting their expressiveness. To overcome these limitations, we propose ConxGNN, a novel GNN-based framework designed to capture contextual information in conversations. ConxGNN features two key parallel modules: a multi-scale heterogeneous graph that captures the diverse effects of utterances on emotional changes, and a hypergraph that models the multivariate relationships among modalities and utterances. The outputs from these modules are integrated into a fusion layer, where a cross-modal attention mechanism is applied to produce a contextually enriched representation. Additionally, ConxGNN tackles the challenge of recognizing minority or semantically similar emotion classes by incorporating a re-weighting scheme into the loss functions. Experimental results on the IEMOCAP and MELD benchmark datasets demonstrate the effectiveness of our method, achieving state-of-the-art performance compared to previous baselines.

Abstract-Emotion Recognition in Conversations (ERC) facilitates a

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Index Terms—Emotion Recognition in Conversations, Graph Neural Network, Hypergraph, Multimodal.

I. INTRODUCTION

Emotion Recognition in Conversations (ERC) has gained significant attention as a research field for its broad practical applications. Traditional ERC approaches primarily focus on classifying emotions within individual utterances using conversational text [1], [2]. Leveraging the continuous nature of utterances in a conversation, some ERC methods model both the semantic features of utterances and the contextual information of conversations. Early approaches like ICON [3], CMN [4], and DialogueRNN [5] employ RNNs to model the conversation as a sequential flow of utterances. Meanwhile, Ada2I [6] tackled the challenge of modality imbalances and modality-fusion learning. However, these methods struggle to effectively balance long- and short-term dependencies for each utterance. In contrast, Graph Neural Networks (GNNs) have gained popularity due to their ability to efficiently aggregate information in conversational contexts. DialogueGCN [7] and RGAT [8] employed GNNs to model inter-utterance and inter-speaker relationships. DAG [9] leveraged the strengths of both traditional graph-based and recurrent neural networks. Recent advancements, such as CORECT [10] and M3GAT [11], integrated modality-specific representations with cross-modal interactions to create more comprehensive models. Additionally, approaches like graph contrastive learning [12], [13] and knowledgeaware GNNs [14] further demonstrated the potential of GNNs to boost performance, setting a new benchmark for future ERC systems.

However, current GNN-based approaches still face limitations in fully capturing conversational context. First, they rely on a fixed window size to model contextual information for all utterances, overlooking the variability in emotional shifts across a dialogue. This fixed setting struggles to account for the different emotional influences of each utterance, as the range of emotional impact varies throughout conversations. Second, traditional GNNs assume pairwise relationships between nodes, while in ERC, the emotional tone of one utterance can influence multiple subsequent utterances, which cannot be effectively captured through pairwise connections alone. Third, the integration of fine-grained multimodal features into emotional state prediction has not been thoroughly explored, limiting the potential performance improvements. Finally, current state-of-the-art (SOTA) methods overlook the issue of class imbalance, where majority classes significantly outnumber minority classes. This imbalance results in suboptimal performance, particularly when predicting emotions from minority classes.

To address these issues, we introduce ConxGNN, a novel framework designed to fully capture contextual information in conversations. At its core, ConxGNN consists of two parallel components: the Inception Graph Module (IGM) and the Hypergraph Module (HM). Recognizing the varying impact of utterances across conversations, and inspired by the use of multiple filter sizes in [15], IGM is built with multiple branches, each using a different window size to model interaction distances between utterances, enabling multiscale context modeling. Simultaneously, we capture multivariate relationships within conversations by constructing a hypergraph neural network. The outputs of these two modules are then passed through an attention mechanism, where attention weights are learned to complement emotional information across modalities. Additionally, to mitigate class imbalance, we introduce a re-weighting term to the loss functions, including InfoNCE and cross-entropy loss. Experiments on two popular ERC datasets demonstrate that ConxGNN achieves best performance compared to SOTA methods. The contribution of this paper can be summarized as follows: (1) We propose ConxGNN, which effectively models both multi-scale and multivariate interactions among modalities and utterances; (2) We design an attention mechanism to integrate fine-grained features from both graph modules into a unified representation; (3) We address class imbalance with a re-weighting scheme in the loss functions; (4) We conduct experiments on the IEMOCAP and MELD datasets, demonstrating that our proposed method achieves SOTA performance across both benchmarks.

II. PROPOSED APPROACH

A. Problem Formulation

Given a conversation consisting of L utterances $U = \{u_1, u_2, \ldots, u_L\}$, where each utterance u_i is spoken by speaker $s_i \in S$ and consists of multi-sensory data: textual (\mathbf{u}_i^t) , visual (\mathbf{u}_i^v) , and acoustic (\mathbf{u}_i^a) modalities:

$$u_i = \{ \mathbf{u}_i^t, \mathbf{u}_i^v, \mathbf{u}_i^a \}, \quad i \in \{1, 2, \dots, L\},$$
(1)

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Fig. 1. Detailed architecture of (A) the proposed ConxGNN, (B) Inception Graph Block, and (C) HyperBlock.

in which $\mathbf{u}_i^{\tau} \in \mathbb{R}^{d_{\tau}}, \tau \in \{t, a, v\}$ with d_{τ} is the dimension size of raw modality features. The ERC task aims to predict the label for each utterance $u_i \in U$ from a set of C predefined emotional labels $Y = \{y_1, y_2, \dots, y_C\}$.

Our proposed architecture is illustrated in Figure 1A. In general, ConxGNN contains five main components: a unimodal encoder, an inception graph module, a hypergraph module, a fusion module, and an emotion classifier.

B. Unimodal Encoder

Following [10], we first capture the utterance-level features of each modality. Specifically, we utilize a Transformer encoder [16] for textual modality and a fully-connected network for visual and acoustic modalities as follows:

$$\mathbf{x}_{i}^{t} = \mathbf{Transformer}(\mathbf{u}_{i}^{t}, \boldsymbol{\theta}_{\text{trans}}^{t}), \qquad (2)$$

$$\mathbf{x}_i^{\tau} = \mathbf{W}^{\tau} \mathbf{u}_i^{\tau} + \mathbf{b}^{\tau}, \quad \tau \in \{a, v\}, \tag{3}$$

where $\boldsymbol{\theta}_{trans}^{t}, \mathbf{W}^{\tau} \in \mathbb{R}^{d_{h} \times d_{\tau}}, \mathbf{b}^{\tau} \in \mathbb{R}^{d_{h}}$ are trainable parameters and $\mathbf{x}_{i}^{t}, \mathbf{x}_{i}^{v}, \mathbf{x}_{i}^{a} \in \mathbb{R}^{d_{h}}$. Additonally, considering the impact of speakers information in a conversation, we incorporate the embedding of speakers' identity and produce the respective latent representations $\mathbf{s}_{i} = \mathbf{Embedding}(S)$, in which $\mathbf{s}_{i} \in \mathbb{R}^{d_{h}}$. We then add speaker embedding to obtain speaker- and context-aware unimodal representation $\mathbf{h}_{i}^{\tau} \in \mathbb{R}^{d_{h}}$ at the *i*-th conversation turn:

$$\mathbf{h}_i^{\tau} = \mathbf{s}_i + \mathbf{x}_i^{\tau}, \quad \tau \in \{t, a, v\}.$$
(4)

C. Inception Graph Module (IGM)

1) Graph Construction: We define $\mathcal{G}(\mathcal{V}_{\mathcal{G}}, \mathcal{R}_{\mathcal{G}}, \mathcal{E}_{\mathcal{G}})$ as the multimodal graph constructed from conversations.

Nodes. Each utterance is modeled as three distinct nodes, corresponding to the representations $\mathbf{h}_i^t, \mathbf{h}_i^v$ and \mathbf{h}_i^a , resulting in a total of $|\mathcal{V}| = 3L$ nodes.

Relations. To capture both inter- and intra-dependencies among modalities, we define two types of relations: \mathcal{R}_{inter} denotes the connections between the three modalities within the same utterance, while \mathcal{R}_{intra} represents the connections between utterances of the same

modality within a given time window. To capture this temporal aspect, we introduce a sliding window [p, f] to control the number of past and future utterances that connected to the current node \mathbf{u}_i^{τ} . Therefore, the two groups of relations can be expressed as follows:

$$\mathcal{R}_{\text{inter}} = \left\{ \left(\mathbf{h}_{i}^{\tau}, \mathbf{h}_{i}^{\nu} \right) | \, \tau, \nu \in \{t, a, v\} \right\},\tag{5}$$

$$\mathcal{R}_{\text{intra}} = \begin{cases} \{ (\mathbf{h}_i^{\tau} \xrightarrow{\text{past}} \mathbf{h}_j^{\tau}) | i - p < j < i, \tau \in \{t, a, v\} \} \\ \{ (\mathbf{h}_i^{\tau} \xrightarrow{\text{future}} \mathbf{h}_i^{\tau}) | i < j < i + f, \tau \in \{t, a, v\} \} \end{cases}$$
(6)

Edges. The edge $(\mathbf{h}_i^{\tau}, \mathbf{h}_j^{\nu}, r_{ij}) \in \mathcal{E}_{\mathcal{G}}; \tau, \nu \in \{t, a, v\}$ represents the interaction between \mathbf{h}_i^{τ} and \mathbf{h}_j^{ν} with the relation type $r_{ij} \in \mathcal{R}_{\mathcal{G}}$. Following [17], we utilize the angular similarity to represent the edge weight between two nodes: $\mathbf{A}_{ij} = 1 - \arccos(\sin(\mathbf{h}_i^{\tau}, \mathbf{h}_j^{\nu}))/\pi$, where $\sin(\cdot)$ is cosine similarity function.

2) Inception Graph Module: The range of emotional influence varies between utterances across different conversations. In contexts with significant fluctuations, shorter interaction distances exert a stronger emotional impact, whereas in more stable conversations, longer distances also contribute to the target utterance's emotional tone. Consequently, determining the optimal sliding window [p, f] for graph construction poses a significant challenge. Drawing inspiration from the usage of multiple filter sizes as proposed in [15], we design multiple graph structures corresponding to n distinct window slides $\mathcal{P} = \{[p_1, f_1], \ldots, [p_n, f_n]\}$. Each graph utilizes a different slide, enabling the parallel learning of multi-scale features, which are subsequently combined to form a comprehensive and rich representation. Figure 1A illustrates the module, while Figure 1B depicts the graph structure of an individual block.

3) Graph Learning: With the objective of leveraging the variations of heterogeneous interactions between utterances and modalities as well as the structure diversity of multiple graph blocks, we employ k-dimensional GNNs (k-GNNs) [18]. Specifically, the representation for the *i*-th utterance at layer ℓ ($0 < \ell \le N_{inc}$) is inferred as follows:

$$\mathbf{g}_{i,(\ell)}^{\tau} = \frac{1}{|\mathcal{N}(i)|} \sum_{r \in \mathcal{R}} \left(\mathbf{W}_{0}^{r} \mathbf{g}_{i,(\ell-1)}^{\tau} + \mathbf{W}_{1}^{r} \sum_{j \in \mathcal{N}_{r}(i)} \mathbf{A}_{ji} \mathbf{g}_{j,(\ell-1)}^{\nu} \right),$$
(7)

where $\mathbf{g}_{i,(0)}^{\tau} = \mathbf{h}_{i}^{\tau}$; $\mathcal{N}_{r}(i)$ is the set of the node *i*'s neighbors with the relation $r \in \mathcal{R}$ and $|\mathcal{N}(i)| = \sum_{r \in \mathcal{R}} |\mathcal{N}_{r}(i)|$; $\mathbf{W}_{0}^{r}, \mathbf{W}_{1}^{r} \in \mathbb{R}^{d_{h} \times d_{h}}$ are learnable parameters. After $\ell = N_{\text{inc}}$ iterations, we feed the output $\mathbf{g}_{i}^{\tau} = \mathbf{g}_{i,(N_{\text{inc}})}^{\tau}$ into a Graph Transformer model [19] to further extract rich representations. The representation is then transformed into:

$$\mathbf{o}_{i}^{\tau} = ||_{h=1}^{H} \big[\mathbf{W}_{2} \mathbf{g}_{i}^{\tau} + \sum_{j \in \mathcal{N}(i)} \alpha_{ij}^{\tau} \mathbf{W}_{3} \mathbf{g}_{j}^{\tau} \big], \tag{8}$$

where $\mathbf{W}_2, \mathbf{W}_3 \in \mathbb{R}^{d_h \times d_h}$ are learnable parameters, and $||_{h=1}^H$ represents the concatenation of outputs from H attention heads. The attention coefficient α_{ij}^{τ} is determined by:

$$\alpha_{ij}^{\tau} = \operatorname{softmax}\left(\frac{(\mathbf{W}_{4}\mathbf{g}_{i}^{\tau})^{\top}(\mathbf{W}_{5}\mathbf{g}_{j}^{\tau})}{\sqrt{d_{h}}}\right),\tag{9}$$

where $\mathbf{W}_4, \mathbf{W}_5 \in \mathbb{R}^{d_h \times d_h}$ are learnable parameters. Finally, we aggregate the representation across every branch of the module, to create a unified representation that capable of capturing multi-scale interactions among modalities and utterances. As a result, we obtain new representation vectors:

$$\mathbf{P}^{\tau} = [\mathbf{p}_1^{\tau}, \mathbf{p}_2^{\tau}, \dots, \mathbf{p}_L^{\tau}], \quad \tau \in \{t, a, v\},$$
(10)

where $\mathbf{p}_i^{\tau} = \frac{1}{n} \sum_{j=1}^n \left[\mathbf{o}_i^{\tau} \right]_j$ and $\mathbf{p}_i^{\tau} \in \mathbb{R}^{d_h}$.

D. Hypergraph Module (HM)

1) Graph Construction: We construct a hypergraph $\mathcal{H} = (\mathcal{V}_{\mathcal{H}}, \mathcal{E}_{\mathcal{H}}, \omega)$ from a sequence of L utterances. Similar to the ones in \mathcal{G} , each node $v \in \mathcal{V}_{\mathcal{H}}$ ($|\mathcal{V}_{\mathcal{H}}| = 3L$) represents a unimodal utterance. We initialize the node embeddings $\{\mathbf{q}_{i,(0)}^t, \mathbf{q}_{i,(0)}^a, \mathbf{q}_{i,(0)}^v\}$ with encoded representations $\{\mathbf{h}_i^t, \mathbf{h}_i^a, \mathbf{h}_i^v\}$ respectively. Different from \mathcal{G} , every hyperedges $e \in \mathcal{E}_{\mathcal{H}}$ ($|\mathcal{E}_{\mathcal{H}}| = 3 + L$) are designed to capture the combined effect of modalities and conversational context, connecting every nodes within the same modality and across different modalities in a same utterance. In this fashion, the constructed hypergraph is able to capture high-order and multivariate messages that are beyond pairwise formulation. Additionally, we introduce learnable edge weight $\omega(e)$ for every hyperedge e, enhancing the representation of complex multivariate relationships.

2) *Graph Learning:* We employ hypergraph convolution operation [20] to propagate multivariate embeddings. Mathematically,

$$\mathbf{Q}^{(l)} = \sigma(\mathbf{D}^{-1}\mathbf{H}\mathbf{W}_e\mathbf{B}^{-1}\mathbf{H}^{\top}\mathbf{Q}^{(l-1)}\boldsymbol{\Theta}), \qquad (11)$$

where $\mathbf{Q}^{(l)} = \{\mathbf{q}_{i,(l)}^{\tau} | i \in [1, L], \tau \in \{t, a, v\}\} \in \mathbb{R}^{|\mathcal{V}_{\mathcal{H}}| \times d_{h}}$ is the input at layer l. σ is a non-linear activation function. $\mathbf{H} \in \{0, 1\}^{|\mathcal{V}_{\mathcal{H}}| \times |\mathcal{E}_{\mathcal{H}}|}$ represents the incidence matrix, $\mathbf{W}_{e} = \text{diag}(\omega(e_{1}), \ldots, \omega(e_{|\mathcal{E}_{\mathcal{H}}|}))$ is the learnable diagonal hyperedge weight matrix, and $\mathbf{D} \in \mathbb{R}^{|\mathcal{V}_{\mathcal{H}}| \times |\mathcal{V}_{\mathcal{H}}|}$ and $\mathbf{B} \in \mathbb{R}^{|\mathcal{E}_{\mathcal{H}}| \times |\mathcal{E}_{\mathcal{H}}|}$ are the node degree matrices and hyperedge degree matrix, respectively. After completing N_{hyp} iterations, the final iteration's outputs are obtained as the multivariate representations:

$$\mathbf{Q}^{\tau} = [\mathbf{q}_1^{\tau}, \mathbf{q}_2^{\tau}, \dots, \mathbf{q}_L^{\tau}], \quad \tau \in \{t, a, v\},$$
(12)

in which $\mathbf{q}_i^{\tau} = \mathbf{q}_{i,(N_{\text{hyp}})}^{\tau}$.

E. Fusion Module and Classifier

After utilizing the two mentioned modules, we combine their outputs by concatenating them to form the final feature representation $\mathbf{f}_i^{\tau} = \mathbf{W}_6[\mathbf{p}_i^{\tau} || \mathbf{q}_i^{\tau}] + \mathbf{b}_6$, where $\mathbf{W}_6 \in \mathbb{R}^{d_a \times 2d_h}$ and $\mathbf{b}_6 \in \mathbb{R}^{d_a}$ are learnable parameters. Given that the textual modality carries more sentiment information [10], we propose a cross-modal attention mechanism to align the other two modalities with the textual features, resulting in fused representations for the text-vision and text-audio

modalities. Specifically, we define the cross-modal attention mechanism as follows:

$$CA_i^{\tau \to t} = Softmax \left(\frac{(\mathbf{W}_Q \mathbf{f}_i^{\tau})^{\top} (\mathbf{W}_K \mathbf{f}_i^{t})}{\sqrt{d_h}} \right) \mathbf{W}_V \mathbf{f}_i^t, \quad (13)$$

where $\tau \in \{a, v\}$. $\mathbf{W}_Q, \mathbf{W}_K, \mathbf{W}_V \in \mathbb{R}^{d_a \times d_a}$ are the query, key, and value weights, respectively. Then, the two fused results were added to the textual features to form a new textual representation after the crossmodal attention:

$$\hat{\mathbf{f}}_{i}^{t} = \mathbf{f}_{i}^{t} + \mathbf{C}\mathbf{A}_{i}^{v \to t} + \mathbf{C}\mathbf{A}_{i}^{a \to t}$$
(14)

We then aggregate the feature representations of the three modalities to create a unified, low-dimensional feature representation using a fully-connected layer and ReLU function:

$$\mathbf{z}_{i} = \operatorname{ReLU}(\mathbf{W}_{z}[\mathbf{\tilde{f}}_{i}^{t} || \mathbf{f}_{i}^{a} || \mathbf{f}_{i}^{v}] + \mathbf{b}_{z}) \in \mathbb{R}^{d_{z}}$$
(15)

Finally, z_i is then fed to a classifier, which is a fully-connected layer, to predict the emotion label y_i for the utterance u_i :

$$\mathbf{p}_i = \operatorname{Softmax}(\mathbf{W}_7 \mathbf{z}_i + \mathbf{b}_7) \tag{16}$$

$$\hat{\mathbf{y}}_i = \arg\max(\mathbf{p}_i) \tag{17}$$

where \mathbf{W}_7 , \mathbf{b}_7 are trainable parameters.

F. Training Objectives

To address the challenge of classifying minority classes during training, it is crucial to mitigate the impact of imbalanced class distributions. Inspired from the approach in [21], we introduce a reweighting strategy that uses the effective number of samples for each class to adjust the loss, resulting in a class-balanced loss. Specifically, for a sample from class c_i with n_i total samples, a weighting factor $w_c(i) = (1 - \beta)/(1 - \beta^{n_i})$ is applied to the loss function, where $\beta \in [0, 1)$ is a hyperparameter. Given a batch of N dialogues, where the *i*-th dialogue contains L_i utterances, the class-balanced (CB) training objectives are defined as follows:

Focal Contrastive Loss. To address the challenge of classifying minority classes, we introduce a novel loss function called Class-Balanced Focal Contrastive (CBFC) loss, which extends the focal contrastive loss [22] by incorporating a class-weight term. This loss aligns pairs with the same emotional labels and maximizes inter-class distances by pushing apart pairs with different labels. The CBFC loss is formulated as follows:

$$\mathcal{L}_{\text{CBFC}} = -\frac{1}{\sum_{i=1}^{N} L_i} \sum_{i=1}^{N} \sum_{j=1}^{L_i} \frac{w_c(j)}{|\mathcal{P}_{i,j}|} \sum_{\mathbf{z}_{i,k} \in \mathcal{P}_{i,j}} (1 - t_{j,k}^{(i)}) \log t_{j,k}^{(i)},$$
(18)

where $t_{j,k}^{(i)} = \frac{\exp(\mathbf{z}_{i,j}^{\top}\mathbf{z}_{i,k}/\tau)}{\sum_{\mathbf{z}_{i,s} \in \mathcal{A}_{i,j}} \exp(\mathbf{z}_{i,j}^{\top}\mathbf{z}_{i,s}/\tau)}$, in which $\mathcal{P}_{i,j}, \mathcal{A}_{i,j}$ denote the anchor's positive and full pair sets.

Cross-Entropy Loss. We adopt a weighted Cross-Entropy (CE) loss to measure the difference between predicted probabilities and true labels:

$$\mathcal{L}_{\text{CBCE}} = -\frac{1}{\sum_{i=1}^{N} L_i} \sum_{i=1}^{N} \sum_{j=1}^{L_i} w_c(j) \sum_{c=1}^{|C|} \mathbf{y}_j^c \log \mathbf{p}_j^c, \quad (19)$$

where \mathbf{y}_{j}^{c} is the one-hot vector of the true label.

Full Loss. We linearly combine focal contrastive loss and Crossentropy loss as follows:

$$\mathcal{L} = \mathcal{L}_{\text{CBCE}} + \mu \mathcal{L}_{\text{CBFC}},\tag{20}$$

where $\mu \in (0, 1]$ is a tunable hyperparameter.

 TABLE I

 COMPARISON WITH PRIOR SOTA METHODS ON IEMOCAP AND MELD.

	Method	Network	Acc (%)	w-F1 (%)
IEMOCAP	DialogueGCN [7]	GNN-based	55.29	55.16
	DialogueRNN [5]	Non-GNN	57.22	55.29
	ICON [3]	Non-GNN	63.10	63.8
	COGMEN [26]	GNN-based	64.02	63.78
	CORECT [10]	GNN-based	66.20	66.39
	ConxGNN (ours)	GNN-based	68.52	68.64
MELD	DialogueGCN [7]	GNN-based	42.75	41.67
	DialogueRNN [5]	Non-GNN	61.88	61.63
	MM-DFN [27]	GNN-based	66.09	64.16
	M ³ Net [28]	GNN-based	65.75	65.00
	ConxGNN (ours)	GNN-based	66.28	65.69

III. EXPERIMENTS AND ANALYSIS

A. Dataset

We conducted experiments on two multimodal datasets: IEMOCAP [23] and MELD [24]. The IEMOCAP dataset consists of 12 hours of two-way conversations involving 10 speakers, comprising a total of 7,433 utterances and 151 dialogues, categorized into six emotion classes: happy, sad, neutral, angry, excited, and frustrated. The MELD dataset includes 1,433 conversations and 13,708 utterances, each labeled with one of seven emotion categories: angry, disgusted, fearful, happy, sad, surprised, and neutral. To ensure a fair comparison, we utilized the predefined train/validation/test splits provided by each dataset. As IEMOCAP lacks a validation set, we followed the split used in recent work [10] for training and validating all methods.

B. Experimental Setups

For both datasets, we use the Adam optimizer [25] with a learning rate of 0.0004 over 40 epochs. The number of layers in IGM and HM for both datasets is set to 2 and 4, respectively. We set $\beta = 0.999$ and $\mu = 0.8$ across both datasets. The IGM architecture comprises 3 GNN branches, with window sizes set to [(10, 9), (5, 3), (3, 2)] for IEMOCAP and [(11, 11), (7, 4), (6, 4)] for MELD. Hyperparameters, including window sizes and the number of layers in each module, are set using the validation set. All reported results represent the mean of five independent runs.

C. Experimental Results

Table I presents a performance comparison between our proposed method and other SOTA approaches. The results demonstrate that ConxGNN achieves superior performance across both datasets. Specifically, ConxGNN surpasses the previous best method, CORECT [10], by 2.32% in accuracy and 2.25% in weighted-F1 score on the IEMOCAP dataset. On the MELD dataset, our model shows slightly improvements of 0.19% in accuracy and 0.69% in weighted-F1 score compared to MM-DFN [27] and M^3Net [21], respectively. These findings empirically validate the effectiveness of our proposed architecture.

D. Ablation Study

1) Components Analysis: We conduct ablation study to evaluate the contribution of each module within our framework. Table II represents the model's performance when specific components are removed. Of the four modules, we can see that IGM has the greatest impact, as its removal leads to a significant performance decline across both datasets, with a drop in (accuracy, weighted-F1) of (27.8%, 42.96%) on IEMOCAP and (15.44%, 25.48%) on

TABLE II PERFORMANCE WITH DIFFERENT STRATEGIES.

Method	IEMOCAP		MELD	
	Acc (%)	w-F1 (%)	Acc (%)	w-F1 (%)
ConxGNN – w/o IGM – w/o HM – w/o crossmodal	68.52 38.48 64.06 64.21	68.64 25.68 63.92 64.31	66.28 50.84 65.11 66.15	65.69 40.21 64.87 65.69
 – w/o crossiliodal – w/o re-weight 	63.13	63.90	65.30	65.10

TABLE III PERFORMANCE WITH DIFFERENT NUMBER OF BLOCKS.

# Blocks	IEMOCAP		MELD	
	Acc (%)	w-F1 (%)	Acc (%)	w-F1 (%)
	65.27	65.34	64.36	62.61
1	65.29	65.31	64.27	62.65
	65.37	65.55	64.70	62.86
	66.30	66.64	65.34	63.49
2	66.02	65.88	65.40	63.44
	66.74	66.91	65.81	63.88
3	68.52	68.64	66.28	65.69

MELD. The second key module, HM, also plays a critical role, especially on IEMOCAP, where its absence results in approximately a 4.5% reduction in performance, though its effect on MELD is minimal, causing around 1% degradation. The removal of other components, such as the cross-modal attention mechanism and the re-weighting scheme, also results in slight performance reductions. These findings collectively confirm the importance and effectiveness of each component in our architecture.

2) Impact of Multi-scale Extractor: To highlight the significance of the IGM, we conduct an ablation study by varying the number of inception graph blocks/branches within the module. Table III presents the best average results for each number of blocks. In the 2-block analysis, we explore different combinations of three sliding windows to evaluate performance. The results are fairly consistent for the same number of blocks. Additionally, performance improves steadily as more blocks are added, with an approximate increase of 1% per block. Compared to the single-scale approach (i.e., a single block), our multi-scale strategy leads to notable performance gains, with accuracy increasing by 3.15% on IEMOCAP and 2.83% on MELD, and weighted F1 improving by 3.09% on IEMOCAP and 2.83% on MELD. These findings underscore the importance of the proposed IGM, which captures multi-scale interactions between modalities and utterances.

IV. CONCLUSION

We propose ConxGNN, a novel framework specifically designed for contextual modeling in conversations for the ERC task. ConxGNN is composed of two primary modules: the IGM, which extracts multiscale relationships using varying interactive window sizes, and HM, which captures the multivariate relationships among utterances and modalities. These modules operate in parallel, and their outputs are combined using an attention mechanism, resulting in contextually enriched information. Additionally, ConxGNN addresses the issue of class imbalance by incorporating a re-weighting scheme into the loss functions. Experimental results on the IEMOCAP and MELD datasets demonstrate that our approach achieves SOTA performance, highlighting its efficacy and advantages.

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