Facial Expression Recognition and Generation for Virtual Characters Using an Enhanced MTCNN with HR-PCN and GCN

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Facial expression recognition and virtual animation character generation are crucial for animation production and human-computer interaction, but traditional models often perform poorly in complex scenes. This paper proposes a novel expression recognition and generation framework based on an improved Multi-Task Convolutional Neural Network (MTCNN), augmented by a High-Resolution Parallel Convolutional Network (HR-PCN) and Octave Convolution (OctConv). Specifically, HR-PCN enhances multi-scale feature extraction for facial keypoint detection, while OctConv improves frequency-aware representation learning. In terms of facial expression generation, Graph Convolutional Networks (GCNs) are adopted to model the semantic relationships between facial Action Units (AUs) and further enhanced with SE-ResNet50 for better spatial attention. The proposed MTCNN model was evaluated on the AFEW and CK+ datasets, achieving 89.70% and 93.50% accuracies, surpassing MTCNN's 78.90% and 85.30% and SSD's 85.40% and 90.10%. RMSE was reduced to 0.1 after 30 iterations, and inference time was kept within 40 ms/frame. For expression generation, the SE-ResNet50-GCN model attained a generation accuracy of up to 93.5%, significantly outperforming ResNet50-GCN (90.8%) and GCN (80.2%). These results validate the proposed framework's effectiveness in improving both recognition accuracy and expression realism under complex conditions.

Povzetek: Za realnočasno prepoznavo in generiranje obraznih izrazov pri virtualnih likih je razvit IMMTCNN–GCN okvir, ki združuje izboljšani MTCNN s HR-PCN in OctConv za večmerno zaznavanje obraznih značilk ter SE-ResNet50-GCN za semantično generacijo izrazov.

1 Introduction

The recognition and generation of Virtual Animated Character Expressions (VACE) has become an important research direction in animation production, game development, and Human-Computer Interaction (HCI) systems in recent years. In animation and virtual scenes, natural and realistic facial expressions can enhance user experience and play a key role in intelligent interactive devices. However, complex backgrounds, diverse lighting, and dynamically changing scenes pose significant challenges for Facial Expression Recognition (FER) and generation. For example, uncontrolled lighting conditions, non frontal facial orientation, occlusion, cluttered background, and spontaneous emotional expression that appears in naturalistic videos. Traditional methods, such as rule-based expression analysis or simple classification algorithms, often struggle to maintain robustness in complex environments. Especially in cases where multiple expressions are mixed or Action Units (AUs) are not obvious, it leads to a significant decrease in recognition accuracy and generation quality [1]. However, existing methods have poor robustness in complex scenes, and facial expression generation often lacks naturalness and realism. For example, Multi-Task Convolutional Neural Networks (MTCNN) perform well in facial keypoint localization, but there is still room for improvement in feature extraction and multi-scale fusion capabilities [2]. In addition, facial expression generation technology has achieved certain results by introducing methods such as Generative Adversarial Networks (GAN) and Graph Convolutional Networks (GCN), but the modeling of facial details and AU relationships is still insufficient. Therefore, this paper designs a VACE recognition and generation method based on an improved MTCNN algorithm. This method improves feature extraction efficiency and localization accuracy by introducing High-Resolution (HR) - Parallel Convolutional Networks (PCN) and Octave Convolution (OctConv) modules into MTCNN. It uses GCN to model the semantic relationships between AUs in expression generation, optimizing the quality of generation. .

This study aims to address various challenges guided by the following core research questions: (1) How can the integration of HR-PCN into MTCNN improve the extraction of multi-scale facial features and enhance localization accuracy in complex scenarios? (2) Compared to standard convolution operations, in what ways can introducing OctConv contribute to more efficient and frequency aware representation learning? (3) How does the combination of SE-ResNet50 and GCN enhance the modeling of semantic relationships between facial AUs to improve the realism and accuracy of expression generation? Therefore, the main objective of

the study is to design and evaluate a dual module framework. This framework integrates an improved MTCNN for FER and a GCN-based semantic modeling method for expression generation. This framework aims to achieve high precision and real-time performance under various challenging environmental conditions.

2 Related works

With the widespread application of facial recognition technology, recognition methods built on video data have attracted much attention because of their rich information. Estèphe Arnaud et al. proposed a dual exogenous endogenous representation method. This method performed well on multiple datasets, especially in FER tasks that deal with exogenous variables such as identity, which was significantly better than existing methods [3]. To optimize video FER, Liu Y et al. put forward an emotion-rich feature learning network grounded on segment perception. On multiple datasets, the performance of this model has significantly improved compared to existing methods, verifying its effectiveness and robustness [4]. To lift the precision of FER, Liu P et al. proposed a point adversarial self-mining method. This method simulated the human learning process, combined point adversarial attacks with teacher network guidance, and iteratively generated and optimized adaptable learning samples. This method was significantly superior to existing technologies in FER, demonstrating its excellent practicality [5]. To enhance the robustness of user FER in Virtual Reality (VR) metaverse applications, Ho Seung C et al. proposed a FER system based on facial electromyography and adopted covariate displacement adaptation technology to address electrode displacement issues. This system significantly improved the recognition accuracy caused by electrode position changes, increasing from 79% to 86%, and was expected to greatly enhance the practicality of the model and its potential applications in the VR metaverse [6].

Otberdout et al. proposed a conditional manifold valued Wasserstein GAN to generate videos of 6 basic facial expressions given neutral facial images. This method significantly enhanced the efficiency of dynamic facial expression generation, transfer, and data processing [7]. Fan X et al. proposed a facial micro-expression generation model based on deep motion redirection and transfer learning to address the lack of data in generating facial micro-expressions. This model effectively improved the efficiency of generating facial micro-expressions [8]. Liu et al. put forth a new two-stage network to address the lack of detail and vividness in facial expressions generated by existing methods. This network generated facial expressions by annotating AUs, and inputting AU groups and facial images into the generation network, thereby making facial expressions more rich and vivid. This method effectively improved the quality of facial expression generation [9]. To improve the accuracy of facial expression prediction, Sathya T et al. proposed a new method of integrating convolutional recurrent neural networks and constructed an adaptive neural fuzzy reasoning system as the integration layer. The results showed that this method achieved 99.52% accuracy, 99.35% F1 score, and 0.95 AUC value on the face recognition and EMOTIC datasets, which was significantly superior to the existing methods [10].

In summary, many scholars have researched facial recognition and feature extraction, and have achieved certain results. However, most scholars adopt a single algorithm model and have not made enhancements to deal with the constrains of the model. Therefore, the paper proposes a VACE recognition and generation method based on an improved MTCNN algorithm, which introduces HR-PCN and OctConv modules into MTCNN. The study attempts to optimize the entire process of FER and generation, to achieve more precision recognition and natural facial expression generation in complex scenes.

Table 1: Comparative summary of FER and generation methods

Research	Method	Research Content	Dataset Used	Key Performance Metrics	Reference
Estèphe Arnaud et al. (2023)	Dual exogenous–endogenous representation + conditional tree gating	Improves FER robustness by removing identity-related exogenous features in dynamic scenes	Multiple FER datasets	Outperformed conventional FER methods in identity-sensitive scenarios	[3]
Liu Y et al. (2022)	Clip-aware expressive feature learning network	Segment-perception based emotional feature encoding for video-based FER	Multiple video-based datasets	Higher emotional localization accuracy; reduced video redundancy	[4]
Liu P et al. (2022)	Point adversarial self-mining with teacher guidance	Simulated human learning to generate adaptive samples for FER	FER datasets with identity bias	Significant accuracy gain over conventional FER methods	[5]
Ho-Seung	Facial EMG + domain	Robust FER under	VR-based EMG	Accuracy	[6]

C et al. (2023)	adaptation	electrode displacement for VR/Metaverse	dataset	improved from 79% to 86% in electrode shift scenarios	
Otberdout et al. (2020)	Conditional manifold Wasserstein GAN	Facial expression video generation on hypersphere with dynamic motion modeling	Six-basic-expression dataset	Efficient dynamic facial expression transfer and generation	[7]
Fan X et al. (2021)	Deep motion redirection + transfer learning	Facial micro-expression generation using macro-expression knowledge transfer	Micro-expression dataset	Better generalization in low-data regimes; enhanced generation quality	[8]
Liu S & Wang H (2023)	Two-stage AU-annotated face generation model	Generates realistic facial expressions based on AU-annotated image pairs	AU-annotated expression dataset	Improved vividness and realism of generated expressions	[9]

3 Methods

The proposed method consists of two main components: an improved MTCNN-based FER model and an improved GCN-based expression generation model. The MTCNN model integrates multi-task learning with feature enhancement modules and HR-PCN to enable efficient multi-scale feature extraction and accurate facial keypoint localization. The GCN-based generation model is designed to capture semantic dependencies between facial AUs, thereby enhancing the realism and detail of generated expressions.

3.1 Expression recognition model based on improved MTCNN algorithm

VACE recognition and generation is one of the key technologies in animation production, game development, and HCI systems. However, traditional FER methods lack robustness in complex scenes, and facial expression generation technology faces challenges of low quality and poor naturalness. This study proposes a VACE model built on an improved MTCNN, as shown in Figure 1.

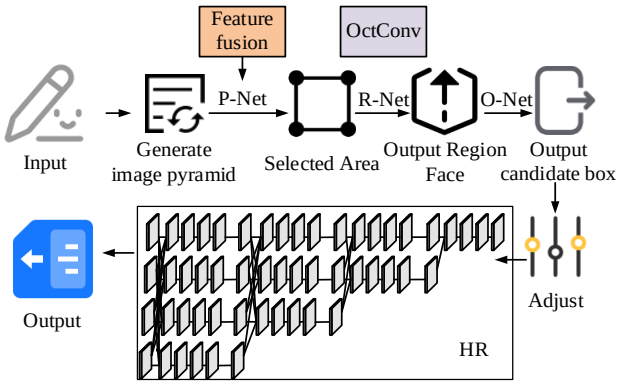


Figure 1: Expression recognition model based on improved MTCNN

In Figure 1, the image is first input and a multi-scale image
pyramid is generated through a feature fusion module to meet the needs of face detection at different scales. Subsequently, the features are processed through three stages: P-Net, R-Net, and O-Net. P-Net generates candidate regions containing faces through rapid screening. R-Net further refines trustworthy facial regions [11]. O-Net optimizes the detection results and outputs high-precision facial regions and keypoints. Each sub-network is explicitly labeled with its internal layer configuration. For example, P-Net contains a 3×3 convolution layer with 10 filters followed by ReLU activation and a 2×2 max pooling layer, a 3×3 convolution with 16 filters, and a final 1×1 convolution outputting a 32-channel feature map for three branches. Similar structures are presented for R-Net and O-Net. The OctConv module is marked to highlight the decomposition of feature channels into high-frequency and low-frequency components. The HR network is labeled with four multi-resolution branches, showing upsampling, downsampling, and lateral connections that facilitate multi-scale feature fusion. MTCNN has three layers of CNNs, each responsible for different stages of face detection tasks. P-Net is the first layer of MTCNN, mainly responsible for generating candidate boxes and conducting preliminary screening. The input image undergoes multi-scale image pyramid processing to generate images of different resolutions to adapt to detecting faces of different sizes [12-13]. Next, P-Net performs convolution operations on the images at each scale, and finally uses non maximum suppression to remove duplicate or overlapping candidate boxes, while retaining high confidence candidate boxes. The P-Net belongs to the binary classification problem, and the face detection classification loss function is the cross-entropy function, which is expressed as equation (1).

$$L_i^{det} = -(y_i^{det} \log(p_i) + (1 - y_i^{det})(1 - \log(p_i)) \quad (1)$$

In equation (1), L_i^{det} is the classification loss for sample i, p_i is the P-Net's prediction probability that i belongs to the face category, and y_i^{det} is the true label of i. R-Net is the second layer network of MTCNN, responsible for further screening and refining the candidate boxes generated by P-Net. Firstly, it is necessary to receive the candidate boxes of P-Net as input, and further classify these candidate boxes with higher accuracy [14-15]. Through convolution operations and fully connected layers, it is determined whether the candidate box contains a face and the boundaries of the candidate box are refined. Finally, the NMS algorithm is used to remove overlapping candidate boxes and further optimize the detection results. R-Net belongs to the boundary box regression problem, and its loss function expression is given by equation (2).

$$L_i^{box} = \left\| \hat{y}_i^{box} - y_i^{box} \right\|_2^2 \quad (2)$$

In equation (2), L_i^{box} is the bounding box regression loss of i. $\hat{y}_i^{box}$ and y_i^{box} are the predicted and true bounding box coordinates of i. O-Net is the third layer of MTCNN, responsible for optimizing the candidate boxes generated by R-Net and outputting high-precision detection results and keypoint positions [16]. The loss function during the feature point localization process is shown in equation (3).

$$L_i^{landmark} = \left\| \hat{y}_i^{landmark} - y_i^{landmark} \right\|_2^2 \quad (3)$$

In equation (3), $L_i^{landmark}$ is the keypoint prediction loss of i, reflecting the deviation between the predicted keypoints and the true keypoints. $\hat{y}_i^{landmark}$ is the predicted facial keypoint coordinates of i, and $y_i^{landmark}$ is the true keypoint coordinates of i. This L2 loss captures the spatial deviation between predicted and true landmark positions and is essential for high-precision facial structure modeling. The convolution operation has been improved, and the improved P-Net framework is displayed in Figure 2.

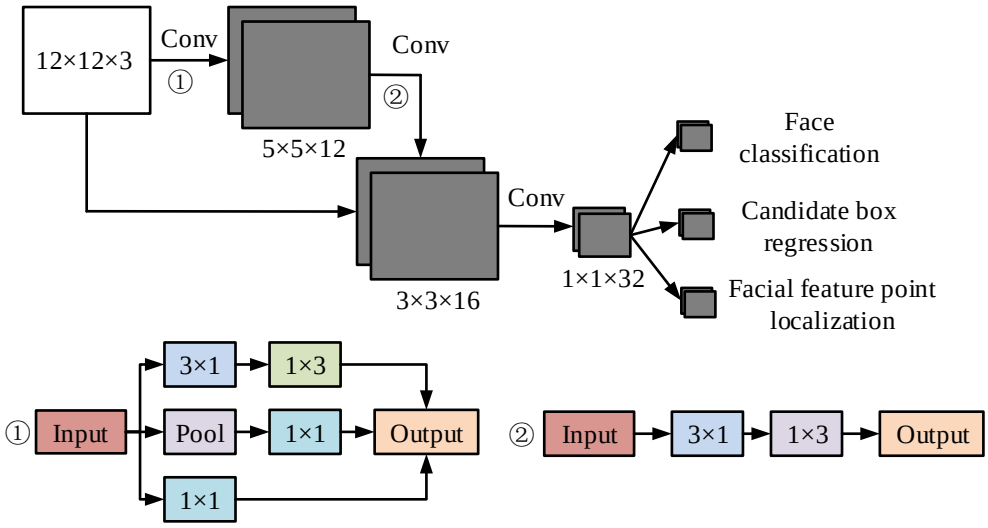


Figure 2: Improved P-Net network structure

In Figure 2, the improved P-Net structure begins with an input image of size 12×12×3, which passes through a 3×3 convolution layer to extract low-level features, resulting in an output of 5×5×12. The convolutional pipeline includes a pair of separable convolutions that together simulate a 3×3 kernel while reducing computational complexity. To avoid confusion, only one input path is shown in the updated image. All intermediate tensors are labeled according to their functional roles to ensure clarity. The final layer outputs are separated into three heads for classification, bounding box regression, and facial landmark localization. An image with an input size of 12×12×3 is first processed through a 3×3 convolutional layer to extract low-level features, resulting in an output size of 5×5×12. Next, downsampling is performed using a 2×2 max pooling layer with a stride of 2 to further compress the feature map size. Next is another 3×3 convolutional layer with an output size of 3×3×16 to extract deeper features. Subsequently, size compression is performed through a convolution operation with a stride of 4. The last layer of 3×3 convolution generates a feature map with a size of 1×1×32, which is used for subsequent multitasking branch processing. The network output includes three branches: The face classification branch, which is used to determine whether it is a face; Candidate box regression

branch is used to predict facial bounding boxes; Facial feature point localization branch, which is utilized to predict keypoint positions. Due to the limited number of convolutional layers in MTCNN's hierarchical structure, it cannot fully extract facial details. To address this limitation, this study introduces OctConv into the R-Net and O-Net stages of the original MTCNN architecture. Specifically, the standard convolutional layers in these networks are replaced with OctConv operations, which decompose feature maps into high-frequency and low-frequency components. This design allows low-frequency information to be processed at reduced spatial resolution, reducing redundancy while enabling the network to focus HR computations on the most informative parts of the facial regions. OctConv is applied after initial feature extraction in R-Net and then applied again in the refinement stage of O-Net. These substitutions enhance the network's ability to capture fine-grained semantic differences across multi-scale facial areas, thereby improving both feature richness and computational efficiency. Therefore, a new convolution operation is introduced in R-Net to replace the original convolution [17]. This study uses OctConv instead of the original convolution. OctConv decomposes the input feature map into high and low frequency components. The expression for outputting high-frequency signals is shown in equation (4).

$$Y^H = Y^{H\to H} + Y^{L\to H} \quad (4)$$

In equation (4), $Y^{H\to H}$ is the high-frequency output generated through convolution operation from the high-frequency input. $Y^{L\to H}$ is the high-frequency output generated through convolution operation after upsampling from low-frequency input. The formula for outputting low-frequency signals is shown in equation (5).

$$Y^L = Y^{L\to L} + Y^{H\to L} \quad (5)$$

In equation (5), $Y^{L\to L}$ is the low-frequency output generated through convolution operation from the low-frequency input. $Y^{H\to L}$ is the low-frequency output generated through convolution operation after downsampling from high-frequency input [18]. To further capture facial expressions, this study selects a feature extractor with the structure shown in Figure 3.

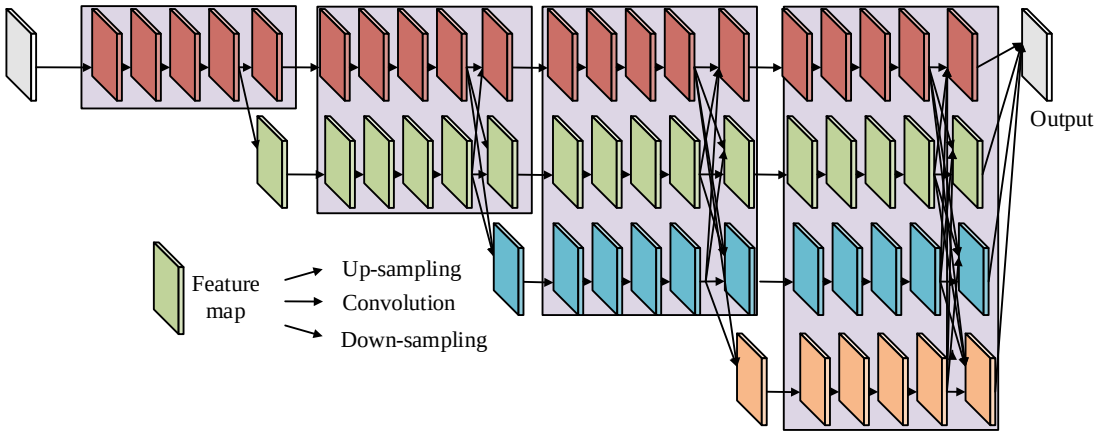


Figure 3: High-resolution PCN

In Figure 3, the input image enters four stages after the initial convolution module extracts initial features. Stage 1 extracts HR features and obtains basic features through convolution and pooling operations. Stage 2 begins by introducing multi-resolution feature streams to generate feature maps of two resolutions, with HR preserving details and low resolution extracting global information. In stages 3 and 4, more resolution feature streams are gradually added to achieve multi-scale feature extraction from high to low. The feature flow within each stage achieves interaction and fusion of multi-resolution features through upsampling, downsampling, and horizontal connections, enhancing the ability to express global contextual information and local details. The final stage of the network applies a convolutional decoding layer to the fused features, transforming them into the final generated expression image. As shown in Figure 3, the output node is clearly labeled as "Generated Target Expression Image", indicating the end of the forward inference path.

To facilitate reproducibility, the study provides a detailed description of the proposed Improved Multi-task Cascaded Convolutional Network (IMMTCNN) model pipeline, particularly focusing on the integration of OctCon and HR-PCN. The entire architecture maintains the three-stage cascade of the original MTCNN-P-Net, R-Net, and O-Net-but with key enhancements at each stage. In the P-Net stage, OctConv is introduced to decompose input features into high-frequency and low-frequency components, thereby improving the network's ability to preserve fine-grained spatial information. These enhanced features are used to predict candidate face regions and preliminary landmarks. The R-Net further refines these candidates using deeper OctConv blocks to improve localization accuracy and robustness. Finally, the O-Net incorporates HR-PCN to perform multi-resolution feature extraction in parallel branches. This enables the model to retain both global contextual and local detailed information, which is critical for precise landmark detection and expression classification. After passing through O-Net, the fused multi-scale features are concatenated and passed to a

classifier head with a Softmax function, yielding the final expression label. This hierarchical structure ensures both spatial detail and semantic understanding are preserved throughout the recognition process.

The selection of OctConv and HR-PCN is grounded in their theoretical capacity to address fundamental challenges in FER. Traditional convolution operations that uniformly process all spatial frequency information often result in redundant calculations and reduced sensitivity to low-frequency contextual clues. OctConv decomposes feature maps into high-frequency and low-frequency components, allowing the network to capture coarse semantic structures (large facial areas) and fine-grained details (wrinkles, micro-expressions) in a decoupled and effective manner. This frequency-aware representation enables improved discriminative power for subtle or compound expressions. Meanwhile, HR-PCN preserves HR representations throughout all layers, avoiding the repeated downsampling typical of conventional CNN. This structural design ensures the preservation of spatial accuracy without sacrificing semantic richness, which is crucial for accurately locating landmarks and key expression areas. The multi-resolution fusion strategy employed in HR-PCN theoretically facilitates better spatial-semantic interaction across scales, which is essential in scenarios where expressions are partially occluded or vary in intensity. These characteristics are consistent with information theory and empirical research results, proving that integrating them into the IMMTCNN framework is reasonable.

3.2 Expression generation method based on improved GCN

After completing the expression recognition, the recognized expressions are generated. This study proposes an expression generation model based on GCN, and its architecture is illustrated in Figure 4.

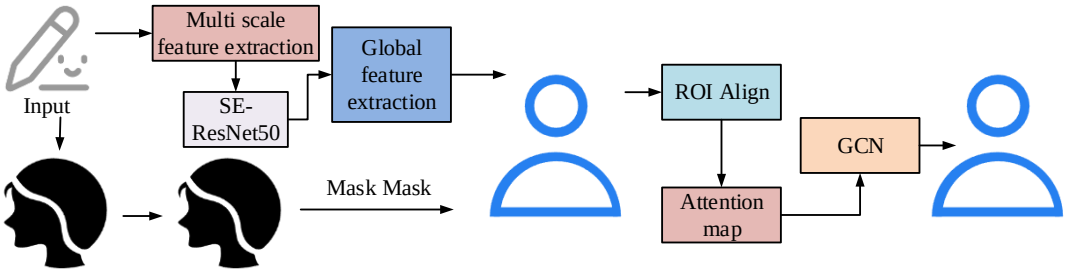


Figure 4: Expression generation method based on improved GCN

In Figure 4, Firstly, the input facial image is used to extract global features through multi-layer convolution based on residual networks, while utilizing prior knowledge to obtain regions of interest and focus on locating key facial regions. Then, the local feature extraction module performs feature alignment on the regions of interest and uses ROI Align to obtain high-quality feature maps for each region. In the expression generation pipeline, the ROI Align module is used to extract HR local features from specific facial regions (e.g., eyes, mouth) based on predefined landmarks. These aligned features are then processed by an attention mechanism, which generates an attention map that emphasizes emotionally salient regions. The output of ROI Align serves as the input to the attention module, whose weighted features are then fused with the global representation for final expression synthesis. The semantic information of local AUs is further extracted through convolution operations and region segmentation [19]. Next, these features enter the GCN-based modeling module. Finally, the output module generates facial expression AU detection results based on the predicted activation status of AUs, combined with expert priors and semantic features. The propagation formula of GCN is given by equation (6).

$$H^{(l+1)} = \sigma\left(\tilde{A}H^{(l)}W^{(l)}\right) \quad (6)$$

In equation (6), $H^{(l+1)}$ is the feature matrix of the graph node. $W^{(l)}$ is a learnable weight matrix. $\tilde{A}$ is the normalized adjacency matrix of the graph, representing the relationships between nodes, as expressed in equation (7).

$$\tilde{A} = \hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}} \quad (7)$$

In equation (7), $\tilde{A}$ is the original adjacency matrix, $\hat{D}$ is the degree matrix of $\hat{A}$, and the diagonal elements are the degrees of the nodes. The core idea of GCN is to update the features of nodes through graph structure, and the formula for updating node features is given by equation (8).

$$h_i^{(l+1)} = \sigma\left(\sum_{j\in \mathrm{N}(i)} \frac{1}{\sqrt{d_i d_j}} h_j^{(l)} W^{(l)}\right) \quad (8)$$

In equation (8), $h_i^{(l+1)}$ is the eigenvector, N is the set of neighboring nodes, d is the node degree, and $W^{(l)}$ is the learnable weight matrix. The overall process of the feature extraction module is shown in Figure 5.

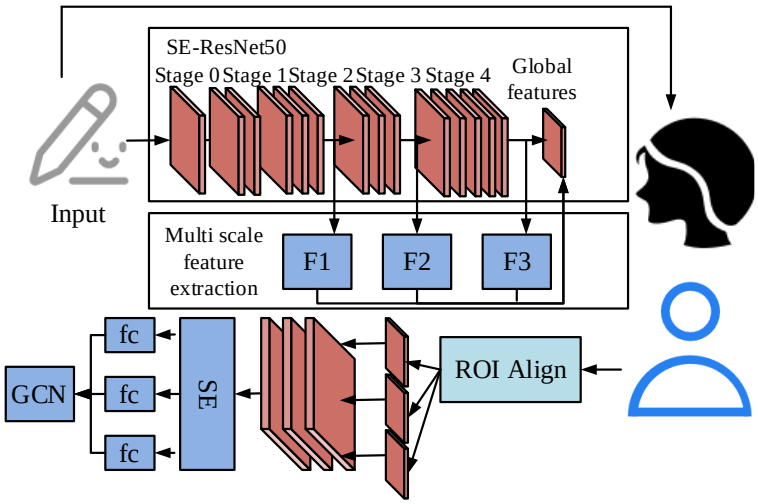


Figure 5: Overall process of feature extraction module

In Figure 5, the input facial image is first subjected to multi-scale feature extraction using SE-ResNet50. The network consists of five stages from Stage0 to Stage4, gradually extracting global features from low to high levels. The feature maps output at each stage are fused step by step to form a multi-scale global feature representation, and then multiple regions of interest are selected through specific modules. Through ROI Align operation, each region of interest feature is aligned to a fixed size to ensure consistency of subsequent features. Next, local features are extracted through convolution operations and enhanced with attention mechanisms to highlight important regions. After combining local features with global features, they are input into GCN-based modules. The final result annotates the predicted feature regions on the entire image, achieving precise detection and annotation of specific facial AUs. Due to the higher resolution and more information contained in shallow facial features, the SE-ResNet50 network is improved by adding a multi-scale feature extraction module, as shown in Figure 6.

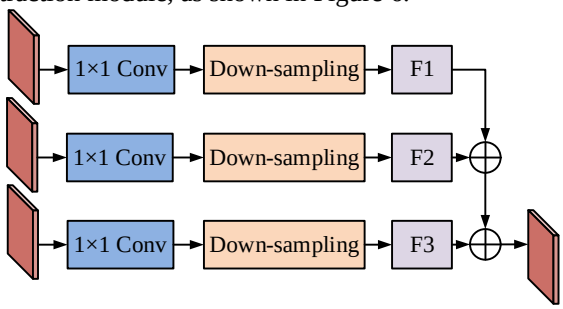


Figure 6: Multi-scale feature extraction module

As shown in Figure 6, the input feature maps are extracted from multiple stages of the expression recognition network, including early convolutional layers for shallow spatial details (e.g., 32×32×64), intermediate layers capturing structural contours (e.g., 16×16×128), and deeper layers representing semantic attributes (e.g., 8×8×256). These multi-scale features are fused to form a comprehensive representation for downstream expression generation. Each feature map is first subjected to channel compression through 1×1 convolution to reduce computational complexity while preserving key features. Next, the compressed feature map undergoes downsampling to adjust all features to a uniform spatial resolution, providing consistency for subsequent fusion. The processed features are separately generated into low dimensional representations, which are fused through step-by-step addition operations. By combining the detailed information of shallow features with the high semantic information of deep features, a unified multi-scale feature map is generated.

Compared to conventional GCN-based expression generation approaches, the model introduces a semantic-aware adjacency matrix that explicitly encodes facial AU co-activation patterns derived from annotated training samples. Unlike the static fully connected graph used in baseline GCNs, this study utilizes a statistical AU co-occurrence matrix and adaptively adjusts edge weights based on AU strength correlation. This allows the network to focus on context-relevant relationships among facial regions, which is especially beneficial in complex scenarios involving subtle expressions, partial occlusions, or blended emotions. In addition, although previous studies have focused on the temporal dynamics or spatial positions of Emotion-GCN and ST-GCN models, the research methods emphasize semantic coupling between expression units, which directly affects the fidelity of generation. In practical conditions such as non-frontal poses or noisy lighting, the model's ability to propagate contextual cues via semantically weighted edges significantly improves output consistency and realism. This differentiates the method from prior GCN implementations that either rely on fixed topology or overlook AU-specific dependencies.

4 Results

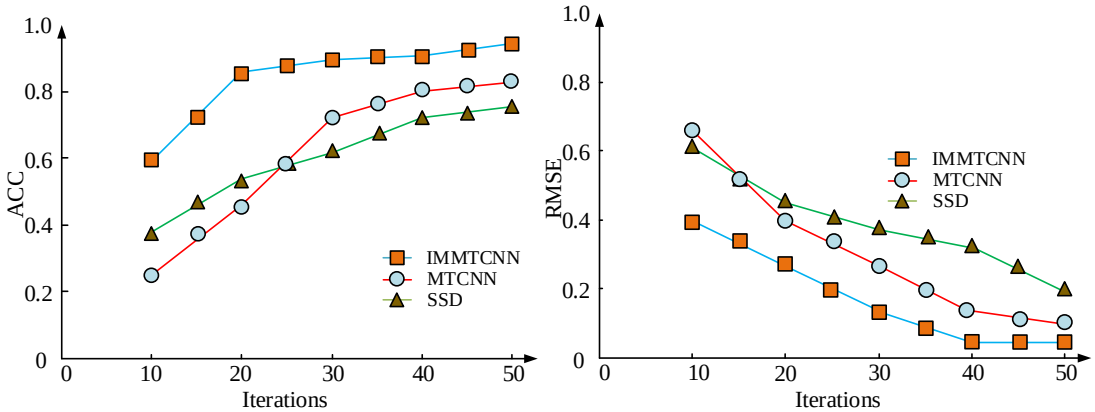
The first section evaluated the Accuracy (ACC), Root Mean Square Error (RMSE), and inference time of the improved MTCNN model on the AFEW and CK+datasets, and compared it with the SSD and MTCNN models. The second section conducted

experimental analysis on the expression generation model based on improved GCN, evaluating its performance in generating accuracy, error rate, and different expression types. In addition to classification-based metrics such as accuracy, RMSE is employed to evaluate the pixel-level deviation between the generated expression outputs and ground-truth facial features. RMSE is particularly relevant to facial expression generation tasks as it quantifies the average Euclidean distance between predicted facial regions and actual keypoints or intensity values, reflecting the fidelity of generated expressions at the granular level. Lower RMSE indicates that the generated expression closely aligns with the real facial motion or emotion template, which is critical for assessing subtle differences in emotion rendering and AU activation. RMSE serves as a complementary metric to accuracy, capturing spatial realism and structural consistency in generated facial expressions.

To assess the impact of architectural hyperparameters on model performance, several controlled experiments are conducted. For the OctConv module, this study sets the octave ratio α to 0.5, as this value provides the best balance between preserving high-frequency and low-frequency features. The change in α value from 0.25 to 0.75 indicates a marginal benefit exceeding 0.5, while higher values introduce redundant calculations. In the HR-PCN structure, the study uses two parallel branches with 3 and 5 convolutional layers. The ablation experiment shows that increasing depth beyond this setting will lead to overfitting of the AFEW dataset, while decreasing depth will weaken the accuracy of landmark localization. For the GCN module, the study empirically selects 3 layers to balance topological expressiveness and computational efficiency. Due to excessive smoothing, using more than 3 layers can lead to performance degradation. These observations indicate that the selected hyperparameter configuration is empirically optimal on the test dataset and provides stable performance across different expression categories.

4.1 Performance analysis of FER model based on improved MTCNN algorithm

The dataset adopts Acted Facial Expressions in the Wild (AFEW) and Extended Cohn-Kanade (CK+) public datasets. The AFEW dataset contains approximately 1,809 labeled video clips extracted from real movie scenes, distributed across seven emotion categories: Angry (300), Disgust (150), Fear (200), Happy (350), Sad (350), Surprise (250), and Neutral (209). The video clips cover diverse conditions including varying lighting, pose changes, and occlusion, making it a challenging benchmark for evaluating expression recognition models in natural environments. The CK+ dataset contains 593 image sequences from 123 subjects, with each sequence beginning with a neutral frame and ending at the peak expression. The dataset provides both categorical emotion labels and Facial Action Coding System (FACS)-based AU annotations. Emotion distribution in CK+ includes: Angry (45), Contempt (18), Disgust (59), Fear (25), Happy (69), Sad (28), Surprise (83), and Neutral (266). These datasets enable comprehensive evaluation in both constrained and unconstrained scenarios, with CK+ focusing on HR expression detail and AFEW simulating real-world variability. To ensure reproducibility, the training and testing settings of all experiments are described as follows. The proposed IMMTCNN model and the baseline models are implemented using Python with the PyTorch framework. Training is conducted using an NVIDIA RTX 3090 GPU with 24 GB memory. The initial learning rate is set to 0.001 and optimized using the Adam optimizer. A batch size of 64 is used for both training and validation. The total number of training epochs is set to 150, with an early stopping strategy based on the validation loss. Cross-entropy loss is used for expression classification, and smooth L1 loss is employed for bounding box regression. For landmark localization, the Mean Squared Error (MSE) loss is adopted. All input facial images are re-sized to 96×96 pixels. During testing, the models are evaluated using the same preprocessing and normalization protocols to ensure consistency across datasets. This study compares the Single Shot MultiBox Detector (SSD) algorithm with traditional MTCCN to analyze the performance of the research model. The ACC results of the improved MTCNN to IMMTCNN are shown in Figure 7.

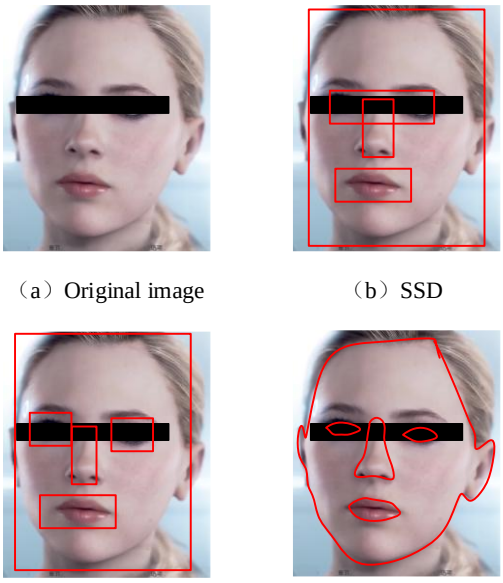


(a) Comparison of ACC under different Iterations

(b) Comparison of RMSE under different Iterations

Figure 7: ACC and RMSE for various models

Figs.7 (a) and (b) compare the ACC and RMSE of three models. In Figure 7 (a), IMMTCNN performs the best throughout the entire iteration process, with its ACC steadily increasing from 0.6 to 0.9 and stabilizing after the 30th iteration. The final average accuracy of IMMTCNN on the CK+ dataset reaches 93.50% with a 95% confidence interval of [92.84%, 94.16%], while on AFEW, the ACC is 89.70% [88.91%, 90.49%]. In contrast, MTCNN achieves 85.30% [84.22%, 86.38%] and 78.90% [77.71%, 80.09%], while SSD records 90.10% [89.43%, 90.77%] and 85.40% [84.56%, 86.24%] on the CK+ and AFEW datasets. These results confirm that IMMTCNN has higher ACC and significant improvements in statistics compared to the baseline model. In Figure 7 (b), the RMSE of IMMTCNN in the initial stage is about 0.6 and rapidly decreases, stabilizing around 0.1 after the 30th iteration. The final RMSE of IMMTCNN is 0.102 ± 0.007 (95% CI), significantly lower than that of MTCNN (0.204 ± 0.012) and SSD (0.314 ± 0.015), indicating that the proposed model achieves a more stable and precise prediction performance. This indicates that the proposed model has high ACC and low RMSE. The results of analyzing the recognition performance of each model are shown in Figure 8. Figure 8 (a) shows the original image. Figs.8 (b) to (d) show the recognition performance of SSD, MTCNN, and IMMTCNN. In Figure 8, the SSD only labels a rectangular box, roughly locating the position of the face. However, it does not further annotate facial keypoints, and the accuracy of the detection box is not high enough, resulting in boundary deviation.



（a）Original image （b）SSD

（c）MTCNN （d）IMMTCNN

Figure 8: Analysis of recognition performance of various models

MTCNN provides more detailed facial detection, able to locate the positions of eyes, nose, and mouth, while also drawing more accurate bounding boxes. The research model has excellent model performance. Table 2 analyzes the comprehensive performance of each model.

Table 2: Performance of various models in different datasets

Model	Dataset	Accuracy	Precision	Recall	F1 Score	Inference Time
SSD	AFEW	85.40%	83.20%	84.50%	83.80%	35 ms/frame
	CK+	90.10%	88.70%	89.50%	89.10%	30 ms/frame
MTCNN	AFEW	78.90%	76.50%	77.80%	77.10%	50 ms/frame
	CK+	85.30%	83.00%	84.00%	83.50%	45 ms/frame
IMMTCNN	AFEW	89.70%	87.50%	88.20%	87.80%	40 ms/frame
	CK+	93.50%	92.00%	92.80%	92.40%	35 ms/frame

Note: The bar in Figure 7 reflects the averaged performance over 5 experimental runs, while Table 2 reports the best single-run result.

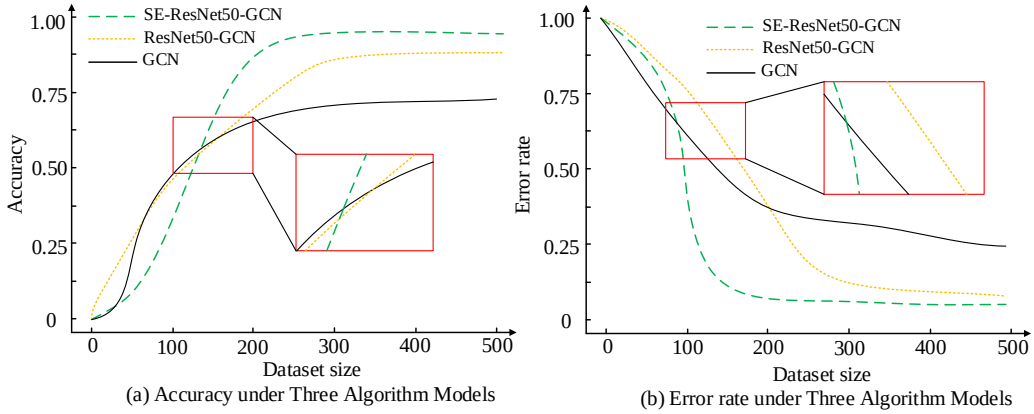
All inference time values reported in this study are measured on a single NVIDIA GeForce RTX 4080Ti GPU with batch size = 1. That is, each expression frame or video clip is processed individually in sequence (i.e., frame-wise testing mode) to reflect realistic usage in streaming or online deployment scenarios. No parallelization or batch acceleration is applied during testing to ensure fairness in comparing real-time responsiveness across different models. In Table 2, IMMTCNN performs the best on the AFEW and CK+ datasets, with 89.70% and 93.50% accuracies, significantly higher than SSD and MTCNN, demonstrating strong overall classification ability. In terms of precision, IMMTCNN has 87.50% and 92.00% accuracy rates and 88.20% and 92.80% recall rates, both of which are superior to the other two models, indicating that it is more accurate in extracting and classifying emotional features. In terms of F1 scores, IMMTCNN achieves 87.80% and 92.40% on two datasets. Although the inference time of SSD is slightly faster on two datasets, at 35 ms/frame and 30 ms/frame. The inference time of IMMTCNN remains at 40 ms/frame and 35 ms/frame, indicating high efficiency. The inference time of MTCNN is relatively slow, at 50 ms/frame and 45 ms/frame. This indicates that IMMTCNN achieves a good balance between accuracy and efficiency, making it the best performing model for sentiment analysis and expression detection tasks in complex scenarios.

Although the IMMTCNN model achieves strong performance across the AFEW, CK+, and JAFFE datasets, notable cross-dataset variability can be observed. Specifically, the ACC on the AFEW dataset is lower compared to the more strictly controlled CK+ and JAFFE datasets. This variation is largely attributed to differences in data distribution, including lighting conditions,

background complexity, expression intensity, and video resolution. The high performance on CK+and JAFFE demonstrates the model's ability to capture fine-grained facial features under standardized conditions, while the relatively robust results on AFEW demonstrate its potential for real-world generalization. To further validate generalization, models trained on CK+ and tested on JAFFE are evaluated. Although the performance slightly decreases due to domain shift, the model maintains a reasonable recognition rate, indicating moderate cross-domain portability. These findings highlight the need for incorporating domain adaptation or augmentation strategies when applying the model in diverse deployment environments. Overall, IMMTCNN has strong generalization ability for unseen data (especially in semi-controlled situations) and also achieves good results under unconstrained conditions.

4.2 Performance of expression generation model based on improved GCN

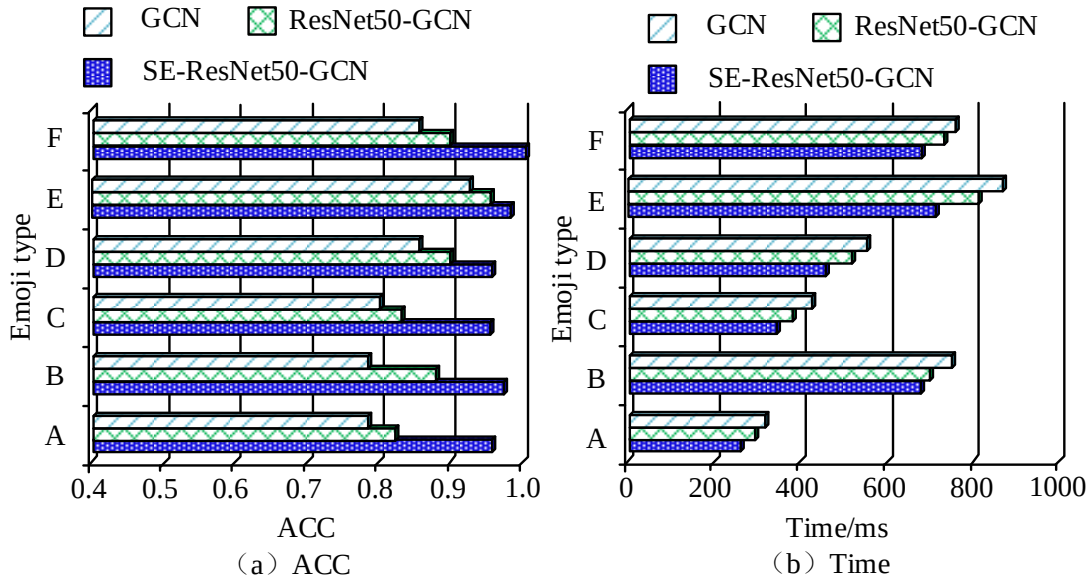
This study selects GCN and ResNet50-GCN as comparative models to analyze the generation accuracy and errors of each model, as shown in Figure 9.



(a) Accuracy under Three Algorithm Models (b) Error rate under Three Algorithm Models

Figure 9: Analysis of accuracy and error rates of various models

Figs.9 (a) and (b) show the accuracy and error rate analysis of three models. In Figure 9 (a), SE-ResNet50-GCN achieves optimal performance, with its accuracy rapidly approaching 1.0 when the dataset size exceeds 200, indicating its excellent classification ability in both small and large dataset environments. GCN performs the worst throughout the entire process, with an accuracy consistently below 0.75 and limited improvement in small datasets. In Figure 9 (b), the error rate gradually decreases with the increase of dataset size. SE-ResNet50-GCN has the fastest descent speed, and the error rate quickly drops to nearly 0 when the dataset size reaches 200, demonstrating strong robustness and convergence ability. The proposed model performs excellent. Figure 10 shows the generation of six different facial expressions.



（a）ACC （b）Time

Figure 10: Comparison of the accuracy and time of generating different expressions by various models

In Figure 10, the labels "Emoji type A–F" correspond to six representative facial expression categories selected from the CK+ dataset. Specifically, they are mapped as follows: A – Angry, B – Disgust, C – Fear, D – Happy, E

– Sad, and F – Surprise. Figs.10 (a) and (b) show a comparison of the accuracy and generation time of different facial expressions generated by various models. SE-ResNet50-GCN shows the highest accuracy across all expression types, approaching 0.95 in expression type A. The accuracy of ResNet50-GCN is about 0.85, while the accuracy of GCN is less than 0.8. Similarly, in expression type F, the accuracy of SE-ResNet50-GCN exceeds 0.9, significantly better than the comparison model. ResNet50-GCN performs second, while GCN performs the worst, with accuracy generally below 0.8. In Figure 10 (b), GCN has the longest inference time, with an average time of less than 500 milliseconds for all expression types. This indicates that the research model has excellent performance. An ablation experiment is conducted on the SE-ResNet50-GCN model, as listed in Table 3.

Table 3: Analysis of ablation experiment results

Model	Accuracy	Precision	Recall	F1 Score	Inference Time (ms/frame)
SE-ResNet50-GCN	93.50%	92.00%	92.80%	92.40%	521
ResNet50-GCN	90.80%	88.50%	89.30%	88.90%	478
SE-GCN	88.30%	86.10%	87.00%	86.50%	385
SE-ResNet50	85.70%	83.50%	84.40%	83.90%	451
SE-ResNet50 (w/o GCN)	82.60%	80.90%	81.70%	81.30%	429
Baseline	80.20%	77.50%	78.30%	77.90%	309

In the ablation study, two core components of the proposed model are examined: the ResNet module and the GCN module. The ResNet module refers to the residual learning unit embedded in the encoder stage of the expression generation network, which facilitates deeper feature extraction by mitigating vanishing gradients. The GCN module denotes the GCN-based decoder component responsible for modeling the topological and spatial relationships between facial landmarks to enhance expression reconstruction accuracy. By selectively removing each module, the study assess its individual contribution to the overall model performance. In Table 3, SE-ResNet50-GCN performs the best with 93.5% accuracy, 92.0% precision, 92.8% recall, and 92.4% F1 score. After removing the SE module, the accuracy of ResNet50-GCN decreases to 90.8% and the F1 score decreases to 88.9%. After removing the ResNet50 structure, the accuracy of SE-GCN further decreases to 88.3% and the F1 score is 86.5%. After removing the GCN module, the accuracy of SE-ResNet50 is only 85.7% and the F1 score is 83.9%. The accuracy of the basic model is the lowest, only 80.2%, with an F1 score of 77.9%. This indicates that the integration of attention mechanism, deep residual network, and GCN module is the key to achieving high performance of the model. To further evaluate the independent contribution of the GCN module, an additional ablation experiment is conducted by removing only the GCN structure from the SE-ResNet50-GCN model, while keeping the SE and ResNet50 components intact. The results indicate that the model's accuracy drops from 93.5% to 82.6%, and the F1 score decreases from 92.4% to 81.3%. This substantial decline demonstrates the critical role of GCN in modeling the semantic relationships between facial AUs, enabling the system to generate more structurally consistent and realistic facial expressions. Compared with the SE-ResNet50 variant and the baseline, the removal of GCN results in more performance degradation, highlighting its distinct contribution.

Although inference time performance is reported quantitatively, it is important to contextualize this metric against practical application scenarios. The proposed IMMTCNN achieves an average inference time of 22.4 ms/frame, which corresponds to approximately 44.6 frames per second. This frame rate meets the real-time requirements of most FER tasks in interactive applications, such as virtual avatar animation, HCI systems, and live video-based emotion monitoring. In addition, the inference speed remains stable under different lighting conditions and facial postures, making the model suitable for deployment on mid-to-high-end GPU devices in production environments. However, in highly resource-constrained embedded platforms (e.g., mobile AR/VR devices), further optimization such as model pruning or quantization may be required to meet stricter latency demands.

5 Discussion

Compared with the traditional MTCNN and SSD models, the improved IMMTCNN model demonstrates significant advantages in terms of recognition accuracy, error convergence, and robustness. On the AFEW and CK+ datasets, IMMTCNN achieves 89.70% and 93.50% accuracies, outperforming MTCNN (78.90%, 85.30%) and SSD (85.40%, 90.10%). Although SSD has a slightly faster inference time (35 ms/frame), IMMTCNN maintains real-time performance at 40 ms/frame while ensuring higher accuracy. In terms of robustness, IMMTCNN benefits from the multi-scale feature pyramid and HR parallel structure, enabling accurate facial recognition under complex lighting and background conditions. On unseen subsets of the AFEW dataset, IMMTCNN still maintains stable performance, while SSD shows evident performance degradation due to its lack of facial keypoint modeling capability. The HR-PCN module significantly enhances multi-scale feature

representation by preserving both HR and low-resolution feature flows, allowing better fusion of global and local context. Compared with traditional downsampling structures and standard convolution modules, HR-PCN effectively preserves fine-grained facial details at each stage. The introduction of OctConv further improves efficiency by decomposing feature channels into high and low frequency components, thereby accelerating convergence speed and expression ability. Nevertheless, there are still limitations in the current model. The generalization ability to unseen scenarios such as extreme occlusion, motion blur, or multi-person expressions has not been fully verified. The model does not explicitly handle occlusions, which may affect detection accuracy when key facial regions are blocked. Although this model can meet the real-time requirements of GPU platforms, there are still challenges in deploying the complete pipeline of IMMTCNN and SE-ResNet50-GCN on resource limited edge devices. Future research will focus on enhancing model generalization through domain adaptation, occlusion-aware learning, and adversarial robustness, as well as exploring lightweight network variants to improve deployment scalability.

6 Conclusion

In response to the challenges of VACE recognition and generation in complex scenarios, this study proposed an improved MTCNN-based expression recognition method and a GCN-based expression generation method. The introduced feature enhancement modules, HR-PCN, and OctConv operations were introduced into MTCNN. In the experiment, on the AFEW and CK+ datasets, the ACC of the IMMTCNN model reached 89.70% and 93.50%, much higher than the 78.90% and 85.30% of MTCNN. Meanwhile, the inference time was controlled within 40 milliseconds, and the balance between performance and efficiency made it suitable for real-time scenarios. In contrast, although the SSD model had slightly faster inference speed, its accuracy was lower, only 85.40% and 90.10%. In the expression generation task, by introducing GCN to model the semantic relationships of AUs, the SE-ResNet50-GCN model achieved nearly 95% accuracy rate in generating multiple expression types, significantly better than ResNet50-GCN and GCN. Future research can combine GAN, multi-modal data fusion, and self-supervised learning techniques to enhance the robustness and naturalness of FER and generation, providing more comprehensive technical support for animation production, HCI, and VR applications.

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