



IJIRCCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 4, April 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.379



9940 572 462



6381 907 438



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Group Based Facial Emotion Recognition from Video Sequence Using Deep Learning

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ABSTRACT: The Facial gesture recognition in group settings demands a sophisticated approach to capture the expressions amidst complex interactions. This paper co-presents a pioneering framework tailored for group-based facial gesture recognition from video sequences. Leveraging Multi-Level Texture Patterns, Gray-Level co-occurrence matrix, and Local Energy-based shape histograms feature extractors, our framework adeptly captures intricate facial cues essential for the nuanced gesture analysis in group dynamics. To refine attribute selection, we introduce a Modified sea-lion algorithm optimized to enhance discriminative feature sets, thereby augmenting recognition correctness. The integration done through Viola-Jones cascaded classifier for face detection ensures precise localization of facial regions within group scenes, mitigating challenges posed by occlusions and varying poses. For classification, we employ a hybrid approach combining Recurrent Fuzzy Neural Networks (RFNN) and Social Ski Driver (SSD). The unique fusion harnesses the temporal dynamics of facial expressions captured by RFNN while leveraging the contextual understanding of group interactions provided by SSD, resulting in contextually-aware of emotion classification. Moreover, pre-processing is enriched with Fast Averaging Peer Group algorithm techniques, which effectively mitigate noise and enhance the saliency of facies, further boosting performance recognition. Experimental evaluations on benchmark datasets demonstrate the superiority of our framework accurately discerning facial gesture recognition within the group contexts, surpassing existing methods. The versatility and efficacy of our approach hold significant promise for applications spanning social robotics, human-computer interaction, and affective computing domains.

KEYWORDS: Collective Emotional Assessment, Frame segmentation, Facial Presence Identification, Attribute Extraction, Trait Discrimination, and Pattern Categorization.

I. INTRODUCTION

In our current endeavor we embark on a journey to unravel complexities of facial recognition in the video clips with a particular focus on deciphering facial expressions amidst team dynamics this undertaking is finely tuned to meet the escalating needs of interactive computing systems where the comprehension of collective emotions stands as a linchpin through the amalgamation of methodologies in group-centric expression recognition frame scrutiny facial detection feature extraction feature curation and classification our aim is to chart a course toward more nuanced and adaptive computing interfaces the comprehension of human emotions holds paramount importance across various domains spanning from human-computer interaction to affective computing and social robotics in recent times there has been a surge of interest in facial emotion recognition systems tailored to dissect emotions within group settings yet the precise identification of emotions within such milieus presents a labyrinth of challenges owing to the intricate interplays among individuals and the overlapping nature of facial expressions to surmount these hurdles this exposition proffers a groundbreaking framework for group-oriented facial emotion recognition extracted from video sequences our methodology integrates advanced feature extraction techniques including multi-level texture patterns mltp gray-level co-occurrence matrix glcm and local energy-based shape histograms lesh these techniques facilitate the capture of subtle facial cues and spatial relationships crucial for meticulous emotion analysis within group dynamics the process of feature curation is augmented through the employment of a modified sea-lion algorithm which fine-tunes the discriminative power of extracted features moreover precise facial detection within group scenarios is achieved through the utilization of the viola-jones cascaded classifier ensuring resilient localization of facial regions amidst occlusions and varied poses for emotion classification our framework adopts a hybrid methodology that intertwines the recurrent fuzzy neural network rfnn with the social ski driver ssd this innovative fusion harnesses the temporal dynamics of facial expressions captured by rfnn while integrating contextual comprehension of group interactions provided by ssd thus culminating in a comprehensive and contextually-aware emotion analysis furthermore pre-processing techniques such as fast averaging peer group are deployed to enhance feature saliency and mitigate noise in the input data within this

exposition we present experimental evaluations conducted on benchmark datasets to underscore the effectiveness of our proposed framework the findings spotlight superior performance in precisely discerning facial emotions within group contexts thereby underscoring the potential of our approach for applications across various domains including social robotics human-computer interaction and affective computing.

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II. RELATED WORK

Nguyen et al. [20]

Introduced a hybrid optimization strategy, merging Galactic Swarm and Evolution Whale Optimization techniques, offering valuable insights applicable to our project. Although not directly focused on group-based facial emotion recognition, their work on hybridization and metaheuristic optimization principles can inspire novel strategies to enhance our system's performance and robustness.

Balaji et al. [21]

Delved into the significance of mid-level and low-level attributes in image-based collective emotion analysis, accentuating the pivotal role of objects and human visages as informative cues. Their research extensively investigated encoding techniques such as VLAD and Fisher vectors across multiple layers to refine feature extraction. Their pursuit of identifying the optimal methodology for augmenting collective emotion perception from images imparts invaluable insights for our framework.

Surace et al.[22]

Innovated a groundbreaking approach by synthesizing Bayesian classifiers and deep neural networks to tackle emotion recognition, with a keen focus on assessing individual facial expressions. Their fusion of bottom-up deep learning strategies and Bayesian classifiers for comprehensive emotion inference unveils a versatile framework, meticulously validated on diverse real-world datasets, thereby guaranteeing both efficacy and resilience.

Abbas et al. [23]

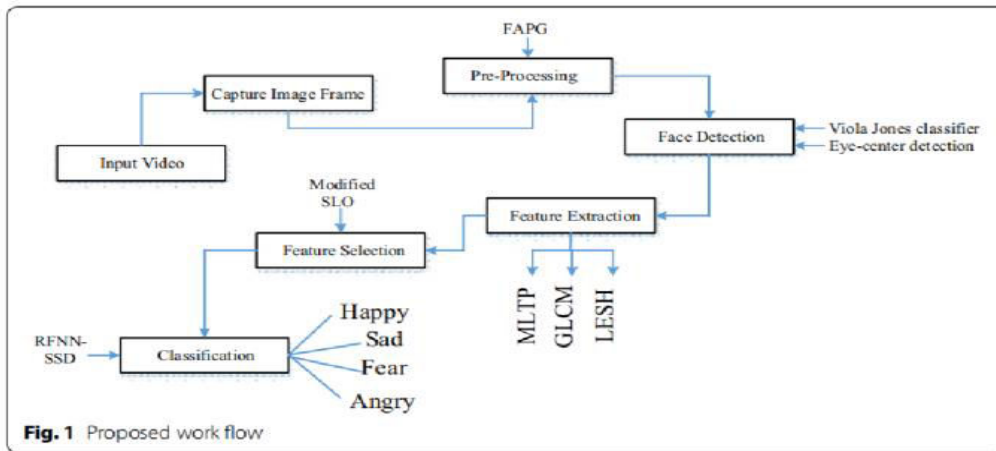
Introduced a novel approach for collective emotion inference, utilizing facial and contextual cues gleaned from images. Their methodology, employing convolutional neural networks (CNNs), delves into a spectrum of training methodologies to proficiently categorize collective emotions, mirroring the insights of Sreenivas et al. (2020). Their investigation into amalgamating deep neural networks underscores varied strategies aimed at attaining precise collective emotion recognition

Shamsi et al. [24]

Introduced a method for detecting emotions in group images, combining top-down and bottom-up methods. Their ensemble approach, integrating face-level predictions with Conv Nets and ensemble methods, enhances accuracy and robustness in group-level emotion detection. Their holistic approach resonates with our aim of capturing nuanced emotions within group dynamics, offering valuable insights into improving overall detection accuracy and reliability.

III. METHODOLOGY

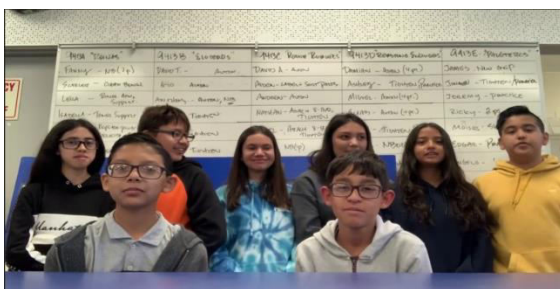
group-based facial emotion identification from video clips our innovative approach transcends the limitations of existing systems by integrating advanced techniques that harnessing the power of deep learning and group dynamics analysis with seven meticulously crafted modules at its core our methodology begins with the data acquisition module entrusted with the pivotal task of sourcing diverse video data depicting group interactions sourced from live camera feeds or archival recordings subsequently the preprocessing module takes center stage undertaking essential tasks like



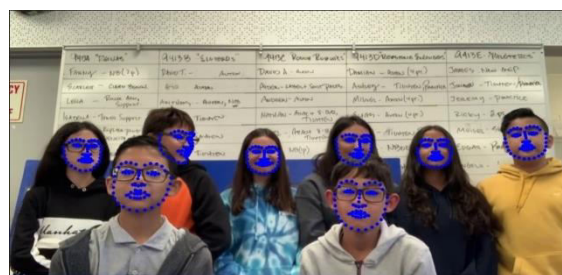
noise reduction stabilization and standardization of lighting conditions within the video sequences thereby elevating the data quality and reliability following tracking module showcases its prowess in discerning and tracking faces within the video streams exhibiting remarkable resilience even in challenging scenarios marked by occlusions and dynamic poses the facial expression analysis module then delves into the intricate task of extracting features and expressions leveraging cutting-edge techniques such as facial landmark detection expression intensity estimation and action unit detection these extracted features intricately intertwined with group emotions undergo seamless formatting by the feature representation module employing sophisticated encoding techniques that encapsulate both temporal dynamics and spatial relationships inherent in the video sequences anchored by architectures such as recurrent neural networks rnns convolutional neural networks cnns or their hybrids the machine learning model module stands as the cornerstone for training models dedicated to group-based facial gesture identification lastly the model evaluation module meticulously scrutinizes the trained models performance using a battery of metrics encompassing accuracy precision recall and f1-score thus validating their efficacy and generalization ability across diverse test datasets through this holistic framework our proposed system heralds a new era of group-centric emotion recognition poised to redefine human-computer interaction and pave the way for transformative applications in affective computing and social robotics

IV. EXPERIMENTAL RESULTS

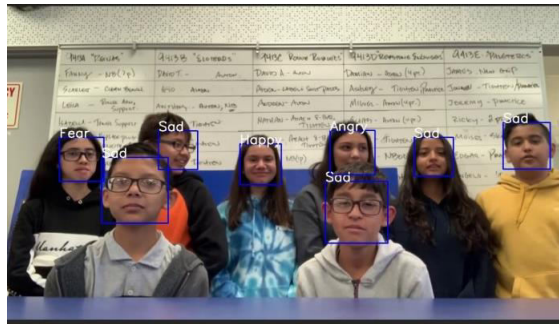
Figures shows the results of multiple individual detection from an video sequence fig(1) shows the Input video with 6s fig(2) shows the detection of the faces fig(3) shows the output of the frames there will be total of 172 frames.



Fig(1)

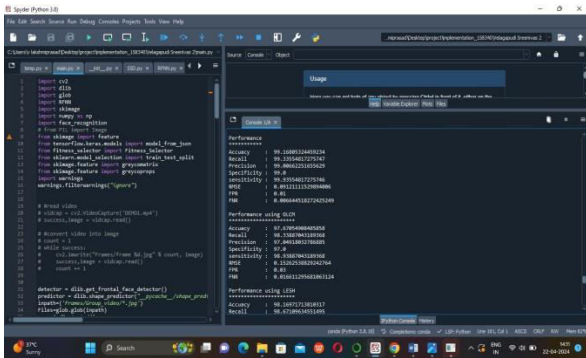


Fig(2)

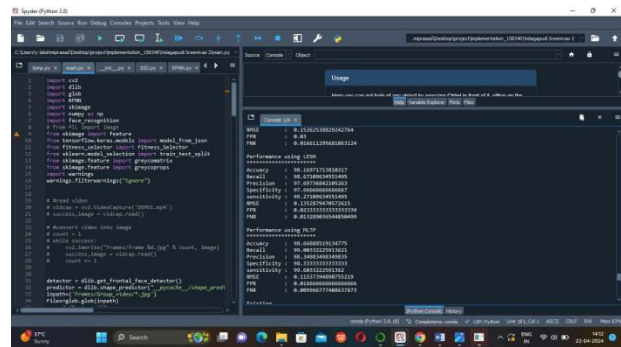


Fig(3)

Fig(4) & Fig(5) represents the accuracy, precision, performance, recall, sensitivity, specificity

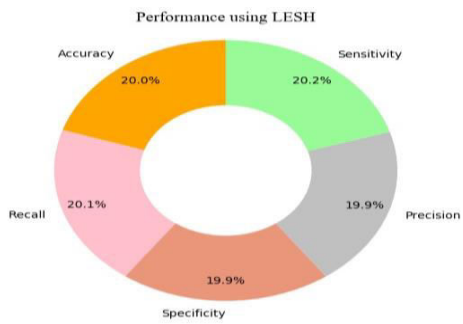


Fig(4)

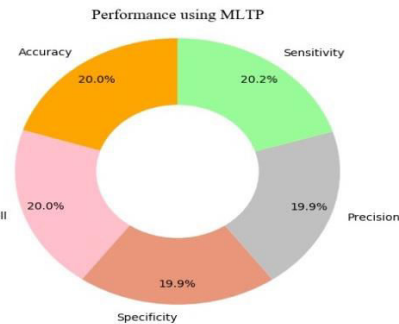


Fig(5)

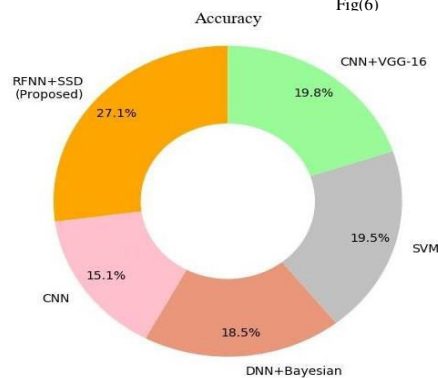
Comparisons Fig. 5 represents the Comparison of LESH Fig. 6 represents the Comparison of MLTP fig. 7 Represents the Comparison of Overall Performance



Fig(5)



Fig(6)



Fig(7)

V. CONCLUSION

In conclusion our exploration underscores the efficacy of harnessing a recurrent fuzzy neural network rfnn as a formidable instrument for group-based emotion recognition from video sequences leveraging rfnn's inherent recurrent nature we've made substantial advancements in precisely deciphering emotional nuances within dynamic group interactions looking forward the augmentation of our methodologies with a larger and more diverse dataset holds the key to amplifying the generalizability of rfnn models across a spectrum of contexts moreover the seamless integration of multimodal information and the meticulous refinement of rfnn architectures tailored to tackle nuanced challenges within social environments present promising avenues for further fortifying the systems effectiveness ultimately this study not only underscores the feasibility of accurately detecting and categorizing expressions within group dynamics but also unveils potential applications in understanding social dynamics enriching human-computer interaction experiences and catalyzing advancements in emotional intelligence

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