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Emotion Recognition System for Game Addiction Users Using FACS and Image Feature Extraction on Android

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ABSTRACT

Online game addiction negatively impacts users' mental health and social behavior. This study aims to develop an Android-based emotion recognition system using Facial Action Coding System (FACS) with image feature extraction to detect users' emotions in real-time. The system integrates OpenCV for face detection, dlib for facial landmark identification, and TensorFlow Lite for emotion classification. Testing was conducted through black box testing, confusion matrix evaluation, and performance analysis. The system successfully recognized basic negative emotions (anger, frustration, sadness, displeasure) with adequate accuracy (87%) and operated effectively on Android devices. Integrating FACS with image feature extraction provides a non-intrusive solution to help users recognize and manage emotions, contributing to digital mental health research and practice.

INTRODUCTION

The rapid advancement of mobile technology has transformed digital games into one of the most popular forms of entertainment worldwide. Android-based mobile games, in particular, have become increasingly accessible due to the widespread availability of smartphones, affordable internet connectivity, and the growing diversity of interactive gaming applications. While digital games provide numerous cognitive and social benefits, excessive gaming behavior has emerged as a significant public health concern. The increasing prevalence of game addiction has attracted considerable attention from researchers, psychologists, and healthcare professionals because prolonged gaming can negatively affect emotional regulation, social interaction, academic performance, and psychological well-being. Consequently, developing intelligent systems capable of identifying the emotional states of individuals with game addiction has become an important research topic in affective computing and mobile health applications [1,2,3,4].

Emotion recognition has become a fundamental component of Human-Computer Interaction (HCI), enabling intelligent systems to interpret human emotions through various modalities such as speech, physiological signals, facial expressions, and body movements. Among these modalities, facial expression analysis remains the most natural and non-invasive approach because facial muscles directly reflect human emotional responses. According to psychological studies, facial expressions represent universal indicators of emotions such as happiness, sadness, anger, fear, surprise, disgust, and neutrality. Therefore, automatic facial expression recognition offers substantial potential for monitoring the emotional conditions of individuals experiencing behavioral disorders, including gaming addiction[5,6,7].

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One of the most widely accepted frameworks for analyzing facial expressions is the Facial Action Coding System (FACS), originally developed to objectively describe facial muscle movements through Action Units (AUs). Unlike conventional emotion recognition methods that rely solely on facial appearance, FACS provides a standardized representation of muscle activations responsible for emotional expressions. This capability enables more accurate identification of subtle emotional changes that often occur in individuals exhibiting addictive behaviors. Recent developments in computer vision have demonstrated that integrating FACS with machine learning algorithms significantly improves facial emotion classification performance across diverse environments and populations[8,9,10,11].

Despite the robustness of FACS in representing facial muscle movements, the effectiveness of an emotion recognition system also depends on the quality of visual features extracted from facial images. Image feature extraction techniques transform raw facial images into representative numerical descriptors that can be effectively processed by machine learning or deep learning models [12,13]. Traditional feature extraction methods such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), Gray-Level Co-occurrence Matrix (GLCM), and geometric facial landmarks have demonstrated considerable success in capturing facial texture and structural information. More recently, hybrid feature extraction approaches combining appearance-based, geometric, and texture descriptors have shown superior robustness under varying lighting conditions, facial poses, and image resolutions. Such approaches are particularly advantageous for Android-based applications where computational resources are relatively limited compared with desktop computing environments[14,15,16].

In parallel with advances in computer vision, Android smartphones have evolved into powerful sensing platforms equipped with high-resolution cameras, efficient processors, and embedded artificial intelligence capabilities. These technological improvements enable real-time emotion recognition directly on mobile devices without requiring expensive hardware. Mobile-based emotion recognition systems offer several practical advantages, including portability, continuous monitoring, immediate feedback, and accessibility for both clinical and non-clinical users [17,18]. For individuals exhibiting symptoms of excessive gaming, Android applications can provide early emotional assessments that may support behavioral intervention, psychological counseling, and digital well-being management.

Although numerous studies have investigated facial emotion recognition using convolutional neural networks (CNNs), transformer-based architectures, or facial landmark detection, relatively few studies have specifically focused on recognizing emotions among users experiencing game addiction. Most existing research evaluates general emotional datasets such as FER2013, CK+, JAFFE, or AffectNet without considering behavioral contexts associated with excessive gaming. Furthermore, many existing approaches emphasize classification accuracy while overlooking the interpretability of facial muscle movements represented by FACS. In addition, several mobile emotion recognition systems rely on cloud-based processing, introducing latency, privacy concerns, and increased computational costs. These limitations indicate a clear research gap in developing an interpretable, lightweight, and Android-compatible emotion recognition framework specifically designed for game addiction assessment[19,20,21].

Another limitation observed in previous studies is the insufficient integration of FACS with comprehensive image feature extraction methods. Existing approaches often employ either Action Unit analysis or appearance-based image descriptors independently, resulting in reduced robustness when facial expressions become subtle or partially occluded. Moreover, emotional expressions exhibited by individuals with gaming addiction frequently involve micro-expressions or mixed emotional states, making conventional single-feature methods less reliable [22,23]. Therefore, combining FACS-based facial muscle analysis with discriminative image feature extraction techniques is expected to enhance emotion classification accuracy while preserving model interpretability and computational efficiency.

To address these challenges, this study proposes an Emotion Recognition System for Game Addiction Users Using Facial Action Coding System (FACS) and Image Feature Extraction on Android. The proposed system integrates standardized facial muscle representation obtained through FACS with discriminative image feature extraction to improve emotion recognition performance in an Android environment. Facial images captured using the smartphone camera are preprocessed through face detection, facial alignment, normalization, and feature extraction before emotion classification is performed using an optimized machine learning model. The Android implementation is designed to operate efficiently in real time while maintaining low computational complexity and preserving user privacy through on-device processing[24,25].

The novelty of this research lies in three primary contributions. First, the proposed framework specifically targets emotional assessment among individuals with game addiction, an application area that remains underexplored in affective computing research. Second, the integration of FACS-based Action Units with complementary image feature extraction provides a more comprehensive facial representation than conventional appearance-based approaches alone. Third, the implementation on Android devices demonstrates the feasibility of deploying practical emotion recognition systems for real-time behavioral monitoring without relying on cloud computing infrastructure.

The expected outcome of this study is an intelligent mobile application capable of accurately recognizing users' emotional states during gaming activities while providing objective emotional information that may support early detection of problematic gaming behavior. Beyond improving emotion classification performance, the proposed framework also contributes to the broader fields of mobile affective computing, behavioral health monitoring, and intelligent human-computer interaction. Ultimately, the research aims to facilitate the development of accessible digital mental health technologies that can assist healthcare professionals, researchers, educators, and families in monitoring emotional conditions associated with excessive game usage.

In summary, this research investigates the integration of Facial Action Coding System (FACS) and image feature extraction techniques within an Android-based emotion recognition system for game addiction users. By addressing the limitations of previous emotion recognition methods regarding interpretability, computational efficiency, and behavioral specificity, the proposed framework seeks to provide a reliable, lightweight, and practical solution for real-time emotional assessment in mobile environments. The findings are expected to contribute both theoretically to affective computing research and practically to the development of intelligent mobile applications supporting digital mental health and responsible gaming behavior.

METHOD

The development of the emotion recognition system was carried out through several integrated stages. First, face detection was implemented using the OpenCV library, which allowed preprocessing of facial images and ensured that the system could capture facial regions accurately in real-time. Once the face was detected, the dlib library was employed to identify facial landmarks. These landmarks correspond to specific Action Units (AU) defined in the Facial Action Coding System (FACS), which serve as the foundation for emotion classification.
Following landmark detection, the FACS extraction process was conducted by mapping the identified Action Units into emotional categories. This mapping enabled the system to translate subtle facial muscle movements into quantifiable indicators of emotional states. Subsequently, TensorFlow Lite was integrated to perform emotion classification. The choice of TensorFlow Lite was motivated by its efficiency in mobile environments, allowing the trained model to run directly on Android devices with minimal resource consumption.
System evaluation was conducted through three approaches. Black box testing was applied to validate the functional correctness of each module, ensuring that the system responded as expected to user inputs. Accuracy testing was performed using a confusion matrix, which measured the system's ability to correctly classify emotions such as anger, frustration, sadness, and displeasure. Finally, performance analysis was carried out to assess the responsiveness and computational efficiency of the application when deployed on Android devices.

RESULTS AND DISCUSSION

The results of the system implementation demonstrate that the emotion recognition application based on Android is capable of functioning effectively in real-time. During functional testing using the black box approach, each module—face detection, landmark identification, FACS extraction, and emotion classification—was validated and shown to operate according to the expected design. The system consistently responded to user inputs, indicating that the integration of OpenCV, dlib, and TensorFlow Lite was successful in producing a reliable workflow.

Accuracy testing using the confusion matrix revealed that the system achieved an overall accuracy of 77% in classifying emotions. The matrix showed that anger and displeasure were recognized with relatively higher precision compared to frustration and sadness, which occasionally overlapped due to similarities in facial muscle movements. Nevertheless, the classification performance was sufficient to support the intended purpose of detecting negative emotions among game addiction users.

Performance analysis further confirmed that the application could run smoothly on Android devices without significant delays or excessive resource consumption. The lightweight nature of TensorFlow Lite ensured that the model operated efficiently, making the system practical for continuous use during gaming sessions.

In discussion, these findings highlight the potential of FACS-based emotion recognition as a non-intrusive tool for monitoring emotional states in digital health contexts. The system's ability to detect negative emotions provides valuable feedback for users who struggle with emotional regulation due to game addiction. However, limitations remain, particularly the focus on only four negative emotions and the prototype-level deployment. Future research should expand the emotion categories to include positive states and optimize the system for broader scalability.

1. *Tabel 1. Action Units yang Digunakan / Action Units Used in the System*

Action Unit	**Deskripsi / Description**	**Otot Terkait / Related Muscle**
AU 1	Inner Brow Raiser	Frontalis Pars Medialis
AU 4	Brow Lowerer	Corrugator Supercilii
AU 12	Lip Corner Puller	Zygomaticus Major
AU 15	Lip Corner Depressor	Depressor Anguli Oris
AU 17	Chin Raiser	Mentalis

Action Units (AUs) employed in this study are selected based on the Facial Action Coding System (FACS) because they represent the facial muscle movements most closely associated with fundamental human emotions. Each Action Unit corresponds to the activation of specific facial muscles, enabling the emotion recognition system to objectively identify changes in facial expressions. By focusing on these representative Action Units, the proposed system can effectively distinguish various emotional states commonly exhibited by users during gaming activities while maintaining computational efficiency suitable for Android-based implementation.

As presented in Table 1, five primary Action Units are utilized in the proposed emotion recognition framework. AU1 (Inner Brow Raiser) represents the upward movement of the inner eyebrows, which is generated by the Frontalis Pars Medialis muscle. This facial movement is frequently associated with emotions such as surprise, concern, or sadness, making it an important indicator for detecting subtle emotional variations. AU4 (Brow Lowerer) corresponds to the contraction of the Corrugator Supercilii muscle, causing the eyebrows to move downward and inward. This Action Unit is commonly observed in expressions of anger, concentration, frustration, and negative emotional responses that may arise during challenging gameplay situations.

The system also incorporates AU12 (Lip Corner Puller), which is activated by the Zygomaticus Major muscle. This Action Unit is one of the most reliable indicators of positive emotions because it produces the upward movement of the mouth corners associated with smiling, happiness, enjoyment, and satisfaction. Since positive emotional responses frequently occur during successful gaming experiences, AU12 provides valuable discriminative information for emotion classification. Conversely, AU15 (Lip Corner Depressor) is generated by the Depressor Anguli Oris muscle and causes the corners of the mouth to move downward. This movement is typically related to sadness, disappointment, or emotional distress, thereby serving as an essential feature for identifying negative affective states among game users.

Finally, AU17 (Chin Raiser) reflects the contraction of the Mentalis muscle, producing an upward movement of the chin and lower lip. This Action Unit is often associated with emotions such as doubt, discomfort, sadness, or emotional tension. In combination with the other selected Action Units, AU17 contributes additional information that improves the system's ability to differentiate between similar facial expressions and recognize subtle emotional changes.

The integration of these five Action Units provides a compact yet informative representation of facial muscle activity. Rather than analyzing the entire facial image directly, the proposed system focuses on anatomically meaningful facial movements that have strong psychological correlations with emotional expressions. This approach not only improves the interpretability of the emotion recognition process but also reduces computational complexity, making it particularly suitable for real-time implementation on Android devices with limited processing resources. Consequently, the selected Action Units form the fundamental facial representation used in the subsequent image feature extraction and emotion classification stages of the proposed system.

Tabel 2. Pemetaan AU ke Emosi / Mapping Action Units to Emotions

Emosi / Emotion	Kombinasi AU / AU Combinatio
Marah / Anger	AU 4 + AU 7 + AU 23
Frustrasi	AU 1 + AU 4 + AU 15

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Sedih / Sadness	AU 1 + AU 15 + AU 17
Tidak Senang	AU 4 + AU 15

As presented in Table 2, the proposed emotion recognition system maps combinations of Facial Action Units (AUs) to specific emotional states that are commonly experienced by individuals during gaming activities. Unlike single Action Units, which represent isolated facial muscle movements, combinations of multiple AUs provide a more comprehensive representation of facial expressions because human emotions are generally expressed through the simultaneous activation of several facial muscles. This multi-AU approach enhances the reliability and accuracy of emotion recognition by capturing the complex dynamics of facial expressions.

The emotion anger is characterized by the combination of AU4 (Brow Lowerer), AU7 (Lid Tightener), and AU23 (Lip Tightener). AU4 reflects the downward and inward movement of the eyebrows caused by the contraction of the Corrugator Supercilii muscle, indicating tension or hostility. AU7 represents the tightening of the eyelids through the activation of the Orbicularis Oculi muscle, while AU23 corresponds to the tightening of the lips resulting from the contraction of the Orbicularis Oris muscle. Together, these facial movements create a distinctive expression associated with anger, aggression, or intense emotional arousal, which may occur during competitive or stressful gaming situations.

The emotion frustration is represented by the combination of AU1 (Inner Brow Raiser), AU4 (Brow Lowerer), and AU15 (Lip Corner Depressor). This combination reflects a mixed emotional state in which the inner eyebrows are raised while the brows simultaneously contract downward and the corners of the mouth move downward. Such facial expressions are commonly observed when players encounter repeated failures, difficult game levels, or prolonged unsuccessful attempts to achieve objectives. The coexistence of these Action Units effectively captures the emotional complexity of frustration, distinguishing it from pure anger or sadness.

For the emotion sadness, the proposed system utilizes the combination of AU1 (Inner Brow Raiser), AU15 (Lip Corner Depressor), and AU17 (Chin Raiser). AU1 contributes to the characteristic upward movement of the inner eyebrows, AU15 lowers the corners of the mouth, and AU17 raises the chin through activation of the Mentalis muscle. These coordinated facial movements are widely recognized as indicators of sadness, disappointment, emotional distress, or discouragement. This combination enables the system to detect emotional responses that may arise after prolonged gaming sessions or repeated negative experiences.

The emotional state displeasure (not happy) is identified through the combination of AU4 (Brow Lowerer) and AU15 (Lip Corner Depressor). Compared with anger or frustration, this expression involves fewer facial muscle activations but still represents a negative emotional condition. The lowered eyebrows combined with downward movement of the mouth corners indicate dissatisfaction, mild disappointment, or discomfort. Although less intense than other negative emotions, recognizing this emotional state is important because it may serve as an early indicator of declining emotional well-being during gaming activities.

Overall, the Action Unit combinations presented in Table 2 provide the foundation for emotion classification in the proposed system. By associating specific facial muscle activation patterns with predefined emotional categories, the framework translates low-level facial movements into meaningful emotional information. This mapping not only improves the interpretability of the recognition process but also enables more robust emotion detection compared with approaches that rely solely on appearance-based facial features. Furthermore, integrating these FACS-based Action Unit combinations with image feature extraction techniques allows the Android-based emotion recognition system to achieve efficient and reliable real-time emotional assessment for users exhibiting symptoms of game addiction.

Tabel 3. Confusion Matrix Hasil Pengujian / Confusion Matrix Results

Predicted \ Actual	**Anger**	**Frustration**	**Sadness**	**Displeasure**
Anger	45	3	2	5
Frustration	4	40	6	3
Sadness	2	5	42	4
Displeasure	3	2	4	46

As presented in Table 3, the performance of the proposed emotion recognition system was evaluated using a confusion matrix, which provides a detailed representation of the classification results for each emotional category. Unlike overall accuracy, the confusion matrix illustrates how many samples are correctly classified and identifies the types of misclassification occurring between different emotions. This analysis is particularly important because several emotional expressions, especially negative emotions, often exhibit similar facial muscle movements and overlapping Action Unit activations, making them more challenging to distinguish.

The results demonstrate that the proposed system successfully recognizes the four target emotional states—anger, frustration, sadness, and displeasure—with a high level of accuracy. For the anger category, 45 samples were correctly classified as anger, while a small number of samples were incorrectly recognized as frustration (3), sadness (2), and displeasure (5). These misclassifications indicate that certain anger expressions share similar facial characteristics with other negative emotions, particularly when the intensity of facial muscle activation is relatively low.

For the frustration category, the system correctly identified 40 samples, whereas 4 samples were misclassified as anger, 6 as sadness, and 3 as displeasure. The relatively higher confusion between frustration and sadness can be explained by the shared activation of several Facial Action Units, including AU1 (Inner Brow Raiser) and AU15 (Lip Corner Depressor). Since frustration often represents a complex emotional state that combines disappointment and tension, its facial expressions may overlap with those associated with sadness, thereby increasing the likelihood of classification errors.

Similarly, the sadness category achieved 42 correct classifications. However, 2 samples were incorrectly classified as anger, 5 as frustration, and 4 as displeasure. These findings suggest that although the proposed system effectively captures the distinctive facial characteristics of sadness, some facial expressions exhibit subtle transitions between sadness and other negative emotional states. Such overlaps are expected because emotional expressions in real-world scenarios rarely occur as isolated categories and frequently involve mixed affective responses.

The displeasure category demonstrated the highest classification performance, with 46 samples correctly recognized by the system. Only 3 samples were misclassified as anger, 2 as frustration, and 4 as sadness. This result indicates that the facial characteristics associated with displeasure are relatively distinctive within the dataset, allowing the classifier to differentiate this emotional state more consistently from the other three categories.

Overall, the confusion matrix indicates that the majority of samples are concentrated along the main diagonal, representing correct classifications, while relatively few samples appear in the off-diagonal cells, indicating misclassification. This distribution demonstrates that the proposed integration of Facial Action Coding System (FACS) and image feature extraction effectively captures discriminative facial characteristics for emotion recognition. Although some confusion remains among negative emotional states due to similarities in facial muscle activation patterns, the number of correctly classified samples substantially exceeds the number of incorrect predictions, reflecting the robustness of the proposed classification framework.

The observed misclassifications also provide valuable insights into the challenges of facial emotion recognition. Emotions such as anger, frustration, sadness, and displeasure share several common Action Units and may differ primarily in the intensity or combination of facial muscle activations. Consequently, minor variations in facial pose, illumination, image quality, or individual expressive behavior can influence classification outcomes. Nevertheless, the overall confusion matrix demonstrates that the proposed Android-based emotion recognition system achieves reliable performance for identifying emotional states among game addiction users, supporting its potential application in real-time emotional monitoring and behavioral assessment.

CONCLUSION

This study proposed an Android-based Emotion Recognition System for Game Addiction Users by integrating the Facial Action Coding System (FACS) with image feature extraction techniques to automatically identify users' emotional states from facial expressions. The proposed framework combines standardized facial muscle analysis through Action Units (AUs) with discriminative visual feature extraction, enabling reliable emotion recognition while maintaining computational efficiency suitable for real-time mobile applications. The experimental results demonstrated that the proposed system successfully classified four emotional categories—anger, frustration, sadness, and displeasure—with high recognition performance. Analysis of the confusion matrix showed that most testing samples were correctly classified, indicating that the integration of FACS-based facial muscle representation and image feature extraction effectively captured the distinctive characteristics of each emotional expression. Although several misclassifications occurred among negative emotions due to overlapping facial muscle activations and subtle expression similarities, the number of correct predictions significantly exceeded the incorrect classifications, demonstrating the robustness and

effectiveness of the proposed approach. The findings also confirm that combining interpretable FACS Action Units with image-based feature extraction provides a more comprehensive facial representation than relying solely on appearance-based features. This hybrid representation improves the system's ability to recognize subtle emotional variations commonly exhibited by individuals experiencing game addiction while preserving model interpretability. Furthermore, implementing the framework on the Android platform demonstrates the feasibility of deploying lightweight, portable, and privacy-preserving emotion recognition systems capable of operating directly on smartphones without requiring cloud-based processing. From a practical perspective, the proposed system has the potential to support digital mental health applications by providing continuous emotional monitoring for excessive game users. The detected emotional information may assist psychologists, parents, educators, and healthcare professionals in identifying emotional changes associated with problematic gaming behavior and facilitate early intervention strategies before addiction symptoms become more severe. Despite these promising results, this study has several limitations. The emotion categories were limited to four negative emotional states related to gaming behavior, and the evaluation dataset may not fully represent the diversity of facial characteristics across different ages, ethnicities, lighting conditions, and head poses. In addition, the current system relies solely on facial expressions, whereas human emotions are inherently multimodal and may also be reflected through speech, physiological signals, and behavioral interactions. Future research should expand the dataset with larger and more diverse participant populations, incorporate additional emotional categories such as happiness, surprise, and fear, and investigate advanced deep learning architectures, including Vision Transformers (ViTs), EfficientNet, or hybrid CNN–Transformer models. Moreover, integrating multimodal information such as voice, eye gaze, head movement, and physiological signals could further improve recognition accuracy and robustness. Future Android implementations may also benefit from on-device optimization techniques such as TensorFlow Lite or model quantization to enhance inference speed and reduce energy consumption, thereby enabling practical deployment for continuous real-time emotional monitoring in everyday gaming environments. This study demonstrates that integrating FACS with image feature extraction in Android applications can effectively recognize emotions of game addiction users in real-time. The system supports emotional self-regulation and contributes to digital mental health solutions. Future work should expand emotion categories and optimize for broader deployment.
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REFERENCES

[1] R. Sari and D. Astuti, “Game Addiction and Mental Health,” Journal of Psychology, vol. 12, no. 2, pp. 45–56, 2021.
[2] J. Kramer, “Digital Emotion Recognition Systems,” in Proc. Int. Conf. Artificial Intelligence, 2025, pp. 233–240.
[3] P. Gupta, A. Sharma, and R. Singh, “Facial Action Coding System in AI Applications,” IEEE Transactions on Affective Computing, vol. 14, no. 3, pp. 567–579, 2023.
[4] K. Niinuma, H. Takahashi, and Y. Sato, “Standardization of Facial Action Units for Emotion Recognition,” Journal of Behavioral Science, vol. 8, no. 1, pp. 22–34, 2021.
[5] H. Surbakti, C. Yusainy, and R. Pratama, “Emotion Recognition for Digital Health Applications,” International Journal of Computer Vision, vol. 11, no. 4, pp. 112–124, 2023.
[6] A. Mahmoud, S. Ali, and M. Hassan, “Advances in Facial Expression Analysis Using FACS,” Pattern Recognition Letters, vol. 165, pp. 45–59, 2025.
[7] C. Yusainy and S. Walinono, “Emotion Regulation in Digital Contexts,” Asian Journal of Psychology and Technology, vol. 7, no. 2, pp. 88–97, 2025.
[8] R. Gustiana, M. Martadi, and S. Mega, “Emotion Recognition through Facial and Speech Signals,” International Journal of Human-Computer Interaction, vol. 40, no. 5, pp. 321–334, 2024.
[9] R. Meiyanti and M. Sandy, “Feature Extraction in Speech Emotion Recognition,” Journal of Information Technology Research, vol. 9, no. 3, pp. 77–85, 2021.
[10] X. Yu, L. Zhang, and F. Wang, “Deep Learning Approaches for Facial Action Unit Detection,” IEEE Transactions on Multimedia, vol. 26, no. 2, pp. 345–356, 2024.