VOL. 11. NO. 1 AUGUST 2025
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480 /jitk.v11i1.6588

JITK (JURNAL ILMU PENGETAHUAN DAN TEKNOLOGI KOMPUTER)

GFPGAN UPSCALING FOR HUMAN FACIAL EXPRESSION CLASSIFICATION USING VGG19 ARCHITECTURE

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Abstract— *Human facial expression recognition is a rapidly evolving field in artificial intelligence and digital image processing. This study aims to develop a model capable of recognizing and classifying human emotions through facial feature analysis. However, a major challenge in facial expression classification is low image quality, which can reduce model accuracy. Factors such as poor lighting, low resolution, variations in viewing angles, and occlusion (obstructions) on the face pose significant obstacles to accurate detection.This research proposes the application of an upscaling method using the Generative Facial Prior Generative Adversarial Network (GFPGAN) to enhance facial image quality by restoring details in expressions that may be unclear due to low resolution. After the upscaling process, facial expression classification is conducted using a CNN architecture based on VGG19, and the model is evaluated using accuracy, precision, recall, and F1-score metrics to assess its performance in emotion detection. Experiments are conducted in two scenarios: classification without upscaling and classification with GFPGAN upscaling. The results indicate that integrating GFPGAN with the VGG19-based CNN proposed in this study significantly improves emotion detection accuracy, achieving 86%, compared to 76% for the model without image quality enhancement.*

Keywords: *Convolutional Neural Network, Facial Expression Classification, Facial Expression Recognition, GFPGAN, VGG19.*

Intisari— *Pengenalan ekspresi wajah manusia merupakan bidang yang berkembang pesat dalam kecerdasan buatan dan pengolahan citra digital. Penelitian ini bertujuan untuk mengembangkan model yang dapat mengenali dan mengklasifikasikan emosi manusia melalui analisis fitur wajah. Namun, tantangan utama dalam klasifikasi ekspresi wajah adalah kualitas citra yang rendah, yang dapat mengurangi akurasi model. Faktor seperti pencahayaan yang buruk, resolusi rendah, serta variasi sudut pandang dan halangan pada wajah menjadi kendala utama dalam deteksi yang akurat. Penelitian ini mengusulkan penerapan metode upscaling menggunakan Generative Facial Prior Generative Adversarial Network (GFPGAN) untuk meningkatkan kualitas citra wajah dengan melakukan restorasi detail pada ekspresi yang kurang jelas akibat resolusi rendah. Setelah proses upscaling, tahap klasifikasi ekspresi dilakukan dengan menggunakan arsitektur CNN berbasis VGG19. Model ini dievaluasi menggunakan metrik akurasi, presisi, recall dan F1-score untuk menilai kinerjanya dalam mendeteksi emosi. Eksperimen dilakukan dalam dua skenario, yaitu klasifikasi tanpa upscaling dan klasifikasi dengan upscaling GFPGAN. Hasil penelitian menunjukkan bahwa integrasi GFPGAN dengan CNN berbasis VGG19 yang diusulkan mampu meningkatkan akurasi deteksi emosi pada wajah manusia secara signifikan sebesar 86%, dibandingkan dengan model tanpa pemrosesan peningkatan kualitas citra sebesar 76%.*

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Kata Kunci: *Jaringan Saraf Konvolusional, Klasifikasi Ekspresi Wajah, Pengenalan Ekspresi Wajah, GFPGAN, VGG19.*

VOL. 11. NO. 1 AUGUST 2025
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INTRODUCTION

In daily life, humans cannot exist without interacting with others. During these interactions, individuals often display facial expressions as a form of communication. Through facial expressions, one can understand the emotions being experienced by an individual [1]. Human facial expressions are one of the most universal and effective forms of non-verbal communication for conveying emotional states [2],[3]. In addition, the ability to recognize emotions is influenced by several factors, such as gender and intensity of human expressions [4]. Human facial expressions can be classified into six basic types: Happiness, Sadness, Surprise, Fear, Disgust, and Neutral [5]. These expressions are not only utilized in human-to-human interactions but also play a critical role in various fields, including psychology, education, and human-computer interaction.

The ability to automatically recognize facial expressions has become an increasingly intriguing topic in the fields of artificial intelligence (AI) and digital image processing, as it can be applied to a wide range of applications, including security, medical diagnosis, and enhancing interactions in modern technologies such as smart devices. Facial expression recognition can assist in diagnosing emotional or mental disorders, such as depression or anxiety [6]. In the security sector, it is used to detect suspicious behavior or stress in individuals monitored by surveillance systems. Additionally, in the entertainment industry, this technology aids in the development of virtual characters for films and video games, enabling realistic facial expressions that significantly enhance the user experience.

Manual facial expression recognition faces several challenges, including variations in facial shapes among individuals, such as differences in size, features, and proportions, making it difficult to apply general feature detection rules. The process of extracting frontal facial regions to identify key features, such as the eyes and mouth, and forming a triangle between the two eyes and the mouth, presents its own challenges, particularly because facial expressions are influenced by viewing angles or facial orientations. Additionally, the "T-zone" of the face, which includes the forehead, eyes, nose, and mouth, plays a crucial role in expression identification [7],[8]. Manual methods relying on static feature detection, such as the distance between the eyes or the shape of the lips, are insufficient to capture subtle changes in facial expressions. Manual recognition processes require significant time and resources, making them inefficient for large-scale data. Therefore, facial image recognition using a Convolutional Neural Network (CNN) approach is essential to overcome the limitations of manual methods, enabling fast and accurate facial expression recognition.

Convolutional Neural Network (CNN) is a machine learning technology that utilizes three hidden layers in its network structure, known as deep learning. This method has proven effective in solving various problems and demonstrates strong performance [9],[10]. With its architecture, CNN models can recognize variations in lighting, facial orientation, and diverse expressions, enabling more accurate and efficient recognition compared to traditional methods. CNN can be optimized for multi-class classification, which is relevant for recognizing various facial expressions, such as happiness, sadness, and anger. In this research, CNN is suitable for handling facial expression recognition cases applied in various fields, including security, healthcare, and entertainment.

In another study [11], using CNN with VGG19 architecture model was also carried out for facial expression recognition. With the application of batch normalization and dropout technology to effectively overcome the problem of over-fitting and improve the model's ability to generalize. This model shows an accuracy increase of 4.52% and a parameter reduction of 45.26%. VGG19 has a simple and uniform Architecture that uses only 3x3 convolutions and 2x2 max-pooling layers, this makes the architecture clean, consistent to extract powerful features from images [12].

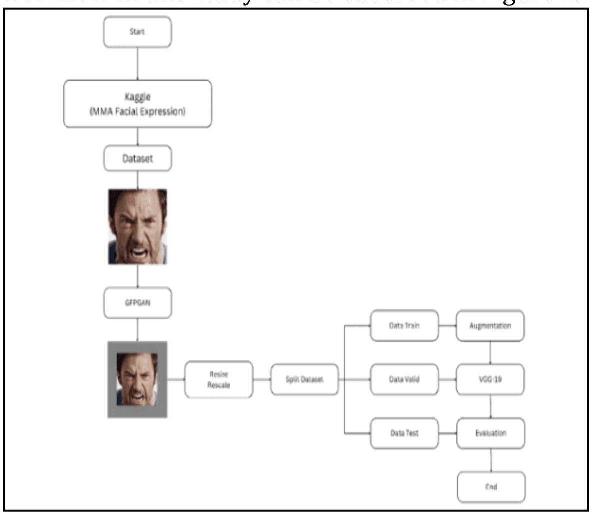
Research [13], provides an overview of GFP-GAN in restoring low-quality facial images while maintaining balance and preserving texture authenticity. This method utilizes Channel-Split Spatial Feature Transform (CS-SFT) to modulate multi-resolution spatial features, enabling more accurate facial detail recovery. Compared to existing techniques, GFP-GAN excels in capturing texture and color information without requiring complex iterative optimization. Experiments demonstrate the effectiveness of this method on datasets of low-quality celebrity facial images and randomly collected facial images from web photos on the internet.

Meanwhile, research [14] develops a cached method that combines degradation removal techniques followed by GFP-GAN to achieve sharper results. This technique proves more effective in handling visual issues such as blurring and JPEG compression in facial images compared to conventional approaches. In addition to enhancing visual quality, this method also helps restore faded colors, making it beneficial for facial expression classification. Experiments on human facial datasets demonstrate significant improvements in detail recovery and facial analysis accuracy..

Based on the outlined problems, this research proposes a Convolutional Neural Network (CNN) method, which is renowned for its effectiveness in image recognition. VGG19 is implemented in this study with the primary objective of not only improving accuracy but also evaluating the performance of the proposed model architecture against positive findings in reference journal. This research also introduces several improvements that distinguish it from previous studies, including the use of a more diverse dataset and the application of pre-processing techniques, specifically upscaling using Generative Facial Prior Generative Adversarial Network (GFPGAN), which has been proven to be specialized for human facial images [15]. With these differences, this study is expected to contribute further to the development of methods for classifying human facial expression images using CNN.

MATERIALS AND METHODS

This research outlines the workflow of the Convolutional Neural Network (CNN) algorithm using the VGG19 architecture to obtain results for facial expression image classification. The system's workflow in this study can be observed in Figure 1.



Source: (Research Results, 2025)
Figure 1. Research Flowchart Diagram

Dataset Collection

The dataset used in this study is sourced from an open-source platform called Kaggle. The researchers utilized a dataset titled "MMA Facial Expression Dataset" [16]. The dataset contains human facial expression images, totaling 3,015 samples, which are divided into three target classes: Angry, Happy, and Sad. Each class is evenly distributed. Figure 2 are examples of human facial expression images for each class.

Source: (Research Results, 2025)
Figure 2. Image Samples for every expression label

Data Pre-Processing

Data preprocessing is a crucial stage in data mining that prepares and transforms data into a suitable format for mining [17]. This stage aims to reduce data volume, detect relationships between data, perform normalization, clean irrelevant data, and extract features using techniques such as cleaning, integration, transformation, and data reduction [18],[19]. In human facial expression classification research, image datasets undergo preprocessing to enhance the quality of data used in model training.

GFPGAN

At this stage, all image datasets will be processed using GFPGAN to enhance resolution. GFPGAN (Generative Facial Prior GAN) is a GAN-based model specifically designed for facial restoration, improving low resolution, noise, and compression artifacts in a single step. By leveraging generative priors from StyleGAN2, GFPGAN can restore realistic details in facial structure, texture, and color, particularly in the eye and mouth areas. Therefore, GFPGAN is highly effective for human faces as it is not designed for other objects, such as landscapes or inanimate objects [8]. Each image will be upscaled individually to produce high-resolution images suitable for training. A comparison before and after resolution enhancement can be seen in the Figure 3.

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P-ISSN: 2685-8223 | E-ISSN: 2527-4864
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Source: (Research Results, 2025)

Figure 3. Before and After Upscaling

Resize Image

In the pre-processing stage of this research, the image size is resized from 512 x 512 pixels to 224 x 224 pixels. This size is recommended by the VGG19 architecture to maintain consistency during the training process, providing a balance between image detail and computational efficiency, as well as ensuring optimal results. Although the image size is reduced, this process retains the relevant information necessary for the model.

Rescale Image

The rescaling process is performed to transform the color range of the images from a value range of 0-255 to 0-1. In this step, each pixel value in the image is divided by 255, ensuring all values fall within a smaller scale, between 0 and 1. This step aims to normalize the image data, making it easier for the model to process, speeding up the training process, and helping improve the model's accuracy in classifying or recognizing patterns in the images [20].

Splitting Data

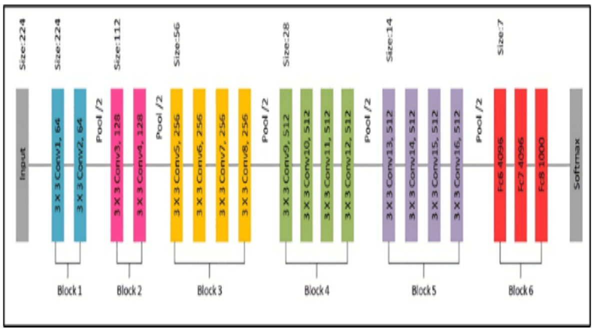
After the pre-processing stage, the data is divided into three parts: training data, validation data, and test data. The distribution is 70% for training data, 15% for validation data, and 15% for test data.

Data Augmentation

Data augmentation is a process used to create more data variations, either by collecting additional data or artificially generating new data [21]. The goal of augmentation is to increase image variations so that the model can be trained on more diverse data, thereby improving the model's accuracy [22],[23]. In this study, data augmentation is performed using various techniques, such as horizontal flip, to enrich data diversity, prevent overfitting, and enhance the model's robustness. The augmentation process includes several additional transformations, such as rotation, shift, zoom, and flip. The combination of these augmentation techniques helps create richer image variations, enabling the model to better recognize patterns and variations in new data..

Model Implementation

VGG19 was developed by the Visual Geometry Group at the University of Oxford and is a deep convolutional neural network architecture with a total of 19 layers. In image processing, this deep learning architecture is typically trained using the ImageNet dataset, which consists of millions of images across 1000 classes. The ImageNet dataset is often used in machine learning competitions [24]. VGG-19 excels in transfer learning due to its deeper architecture with 19 layers, enabling the model to extract more complex and in-depth visual features from images [25]. The VGG-19 architecture used in this study consists of 16 convolutional layers, 4 max pooling layers, 2 fully connected layers, and 1 softmax layer [26]. The convolution structure uses a 3x3 kernel and adopts the ReLU (Rectified Linear Unit) activation function, with an input image size of 224x224 pixels [27],[28]. The detailed architecture of the VGG19 CNN can be seen in the Figure 4.



Source: (R. Shinta, Jasril, M. Irsyad, F. Yanto, and S. Sanjaya [29], 2023)

Figure 4. Structure of the VGG19 Architecture

Model Evaluation

Evaluating the model using the VGG19 architecture is crucial to assess its reliability and overall performance. This involves dividing the dataset into training, validation, and testing data. After training, the model is tested using validation data to measure accuracy, precision, recall, and F1-score. A confusion matrix is used to evaluate the model's ability to distinguish between difficult classes. The evaluation results allow for comparisons with previous studies and help illustrate the model's performance in detail. In testing using the confusion matrix, several calculations are performed [30], namely :

a. Accuracy

The proportion of correct predictions relative to the total data is accuracy. This metric is chosen due to the balanced distribution of data between

VOL. 11. NO. 1 AUGUST 2025
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480 /jitk.v11i1.6588

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the two classes. A higher accuracy value indicates better model performance.

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+FP+FN+TN}} \quad (1)$$

b. Precision

Precision is the ratio of correctly predicted positive instances (true positives) to the total predicted positives (true positives + false positives). A higher precision value indicates better model performance.

$$Precission = \frac{\text{TP}}{\text{TP+FP}} \quad (2)$$

c. Recall

Recall is the ratio of correctly predicted positive instances (true positives) to the total actual positives (true positives + false negatives). A higher recall value indicates better model performance.

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \quad (3)$$

d. F1-Score

The F1-score combines precision and recall, considering both false positives and false negatives. It is defined as 2*(precision*recall divided by the sum of precision and recall. A higher F1-score is desirable, with the ideal value being 1.

$$\text{F1} - \text{Score} = \frac{2\times(\text{Recall}\times\text{Precission})}{\text{Recall+Precission}} \quad (4)$$

Model evaluation also includes observing the results of the model's processing of human facial expression images, as shown in Table 1.

Table 1. Classification Testing

	Predicted Value	
Actual Value	TRUE	FALSE
TRUE	TP	FP
FALSE	FN	TN

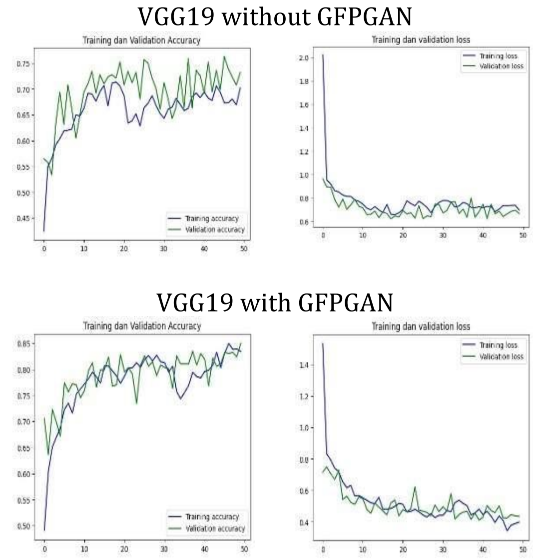
(Research Results, 2025)

Description :
TP : Number of correctly predicted positive samples.
TN : Number of correctly predicted negative samples.
FP : Number of negative samples incorrectly predicted as positive.
FN : : Number of positive samples incorrectly predicted as negative.

RESULTS AND DISCUSSION

Evaluation

In this study, two experiments were conducted to compare image classification results based on image resolution. The first experiment used the original dataset without undergoing the upscaling process, while the second experiment used a dataset that had undergone upscaling to enhance image resolution. In both experiments, the pre-processing methods and classification model remained the same, ensuring that the measured differences were solely due to changes in image resolution, i.e., between low-resolution (Low Resolution) and high-resolution (High Resolution) images. The goal of these experiments was to determine how differences in image resolution affect the accuracy of image classification.



Source: (Research Results, 2025)
Figure 5. Accuracy and Loss Graphs of the Model

Figure 5 illustrates the results of the VGG19 model training process for the two types of data previously described. The model training was conducted using a maximum of 50 epochs. In the first experiment, using images without upscaling, the training and validation accuracy and loss graphs indicate good learning progress, though some fluctuations warrant attention. At the beginning of training, the training accuracy increased significantly from 0.43 to 0.60, while the training loss decreased from 2.0 to around 1.0. The validation accuracy also increased, albeit inconsistently, and the validation loss tended to decrease with varying patterns. Around epochs 10–30, the training accuracy gradually increased to

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P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480/jitk.v11i1.6588

0.70, while the validation accuracy showed unstable changes, indicating the model began to struggle in understanding image values. Both training and validation loss stabilized around 0.7–0.8, although the validation loss exhibited more variability. Toward the end of training, between epochs 30–50, the training accuracy remained around 0.70–0.72, while the validation accuracy fluctuated between 0.65–0.75. The training and validation loss stabilized around 0.6–0.8, indicating that the model had reached stability.

In the second experiment using images with upscaling, the model demonstrated good progress during training. Initially, the training accuracy increased significantly from 0.50 to 0.70, while the validation accuracy also rose, albeit inconsistently. At the same time, the loss values decreased significantly, indicating that the model began to learn patterns effectively. Around epochs 10–30, the training accuracy continued to rise, approaching 0.80, while the validation accuracy remained stable despite minor fluctuations.

The loss also continued to decrease and stabilized around 0.4–0.50. Toward the end of training, between epochs 30–50, the training accuracy reached approximately 0.85, and the validation accuracy was nearly the same, indicating that the model could recognize the data well. The loss also became smaller and stabilized below 0.40. Overall, the model performed well, even though the loss value remained around 0.40.

Prediction results of VGG19 without using GFPGAN

The results of the model without upscaling show an accuracy of 76%, with the best performance in the angry and happy categories, each achieving a precision of 0.88 and an F1-score of 0.79–0.82. Meanwhile, the sad category has a lower precision of 0.51 but a relatively high recall of 0.81. For more details, refer to Table 2.

Table 2. Classification Report for VGG19 without Upscaling

Category	Precision	Recall	*F1-score*
Angry	0.88	0.72	0.79
Happy	0.88	0.76	0.82
Sad	0.51	0.81	0.63

Source: (Research Results, 2025)

The prediction results of human facial images using VGG18 without GFPGAN resulted in 111 misclassified images, An example of an image that was misclassified without upscaling can be seen in Figure 6.

Source: Research Results, 2025
Figure 6. Predictions of VGG19 without GFPGAN

Prediction results of VGG19 using GFPGAN

The results of the model with upscaling show a significant improvement in accuracy, reaching 86%, which is better compared to the model without upscaling. The happy category demonstrates the best performance with a precision of 0.91, recall of 0.87, and F1-score of 0.89. The angry category also performs well with a precision of 0.88, recall of 0.82, and F1-score of 0.85. Meanwhile, the sad category shows significant improvement in recall and F1-score, indicating that the model is better at recognizing human facial expressions. For more details, refer to Table 3.

Table 3. Classification Report for VGG19 with Upscaling

Category	Precision	Recall	*F1-score*
Angry	0.88	0.82	0.85
Happy	0.91	0.87	0.89
Sad	0.78	0.88	0.83

Source: (Research Results, 2025)

Despite the significant improvement after the upscaling process was applied to the data, there are still some prediction errors in the images. Prediction results of human facial images using VGG19 with GFPGAN resulted in 65 misclassfied images. The number of images incorrectly predicted by the model without upscaling and with upscaling can be seen in the Figure 7.

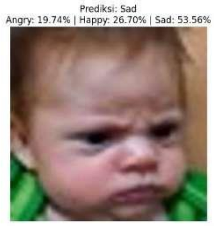
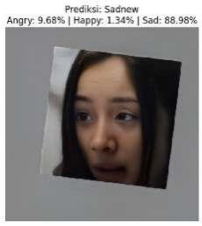
Source: (Research Results, 2025)
Figure 7. Predictions of VGG19 with GFPGAN

Comparison Analysis Results

Several prediction errors that could not be resolved by the model without upscaling were successfully predicted correctly after the upscaling process was applied. Table 4, are some random examples of images from each category that were misclassified by the model without upscaling but correctly predicted by the model with upscaling.

VOL. 11. NO. 1 AUGUST 2025
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
DOI: 10.33480 /jitk.v11i1.6588

Table 4. Comparison Results of VGG19

Misclassification Results Without Using GFPGAN	Correct Classification Results After Using GFPGAN
	
	
	

Source: (Research Results, 2025)

The accuracy results obtained from the experiments using VGG19 can be seen in the following Table 5.

Table 5. Analysis and Accuracy Comparison Results

Experiment	Accuracy (%)
CNN [31]	63%
VGG19 without GFPGAN	76%
VGG19 with GFPGAN	86%

Source: (Research Results, 2025)

It can be observed that the model's accuracy has significantly improved compared to previous studies. In earlier research, the accuracy achieved was lower, whereas in the latest experiment using the VGG19 architecture, the accuracy increased to 86%. This improvement was achieved through the implementation of GFPGAN, an upscaling technique specifically designed to enhance image resolution, particularly for human facial images. GFPGAN helps refine image details by producing clearer and sharper images, making it easier for the model to recognize and classify facial expressions more accurately. Therefore, the combination of VGG19 and GFPGAN significantly contributes to the enhanced performance of the model in facial expression recognition tasks.

CONCLUSION

This study implements the Convolutional Neural Network (CNN) method with the VGG-19 architecture to classify human facial expression images. The dataset used consists of 3,015 facial images evenly distributed across three expression classes: angry, happy, and sad. Before the training phase, the facial images underwent preprocessing, including image upscaling using GFPGAN to enhance image quality and ensure better data consistency and quality for model training. Additionally, the dataset was divided into training, validation, and testing sets, facilitating efficient model training and enabling the evaluation of the model's performance in recognizing facial expressions.

The study conducted two experiments involving two types of data: data without upscaling and data with upscaling. The results for the data without upscaling achieved an accuracy of 76%. In contrast, the data processed with GFPGAN upscaling showed a significant improvement, achieving an accuracy of 86%. However, despite the increase in accuracy, some images were still misclassified due to their poor initial quality, making it challenging for GFPGAN to process them effectively. This indicates that image resolution plays a significant role in human facial expression classification tasks.

The results of the research on the developed model are expected to be applied to various things, for example in tracking emotional well-being in mental health apps or therapy, regularly assesses user's expressions during app interactions.

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VOL. 11. NO. 1 AUGUST 2025
P-ISSN: 2685-8223 | E-ISSN: 2527-4864
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