Feature Extraction Techniques for Facial Expression Recognition (FER)

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Abstract

Facial expression recognition (FER) is a significant area of study in computer vision and affective computing. In numerous applications, such as human-computer interaction, emotion detection, and behavior analysis. Feature extraction is a crucial stage in facial expression recognition systems, as it involves extracting pertinent information from facial images in order to accurately represent various facial expressions. The purpose of this paper is to investigate and compare the various feature extraction techniques used in facial expression recognition, as well as their merits, limitations, and impact on overall system performance. Using benchmark datasets and performance metrics, the evaluation provides insight into the efficacy of various feature extraction methods. In this study, we propose a method for facial expression recognition that integrates deep learning, Principal Component Analysis (PCA), and Gray Level Co-occurrence Matrix (GLCM). Use 1D-CNN for classification.

Keywords- Feature extraction, Handcrafted method, Deep learning method, fisher Vector Encoding**.**

I. INTRODUCTION

Facial expressions are essential for communicating emotions, intentions, and social signals and play a fundamental role in human communication. Humans have an inherent ability to recognize and interpret facial expressions, but automating this process has been a long-standing challenge in the field of computer vision [1]. Facial expression recognition (FER) has attracted a great deal of interest as a result of its vast array of applications, which include human-computer interaction, emotion detection, deception detection, psychological research, and behavior analysis [2]. Feature extraction is a crucial phase that seeks to extract discriminative and representative information from facial images, allowing for the accurate recognition and interpretation of various facial expressions [3]. Binary Patterns (LBP), a popular local descriptor, has gained attention in the scientific community for its role in feature extraction. As one of the earliest descriptors, LBP has evolved into various variants, shaping the field of feature extraction and pattern recognition [4]. Here are additional specifics regarding the significance of feature extraction in facial expression recognition:

1. Dimensionality Reduction: Facial images are typically comprised of high-dimensional data with a large number of pixels. In order to reduce the dimensionality of these images, feature extraction techniques transform them into a lower-dimensional feature space. This reduction not only conserves computational resources, but also focuses on extracting the most informative and discriminatory features of facial expressions, such as Principal Component Analysis (PCA) [5].
2. Discriminatory Representation: Variations in facial features and distinct patterns help to distinguish facial expressions. The goal of feature extraction methods is to identify these distinctive patterns by extracting pertinent data pertaining to the underlying emotions. By representing facial expressions in a discriminative feature space, the recognition system can differentiate between distinct emotions with greater precision [6].
3. Noise Reduction: Facial images typically contain noise, such as variations in illumination conditions, facial aspect, and pose. Feature extraction techniques can help mitigate the effects of noise by accentuating the most prominent and pertinent facial characteristics and minimizing the influence of irrelevant factors [7].
4. The extraction of features reduces the computational complexity of facial expression recognition systems. By transforming high-dimensional input data into a lower-dimensional feature space, subsequent analysis and classification

steps become more efficient, enabling real-time or near real-time processing, which is essential for a variety of applications such as human-computer interaction and emotion-based interfaces[8].

5. Invariance to Irrelevant Factors: Feature extraction methods aim to extract facial expression-related information while maintaining invariance to factors that do not contribute to the expression itself. By extracting features related to the relative positions of facial landmarks, for instance, the system can remain insensitive to changes in facial appearance caused by factors such as age, gender, and ethnicity that are unrelated to the expression being analyzed [9].

There are still many obstacles and opportunities for future research, the most significant of which are the Scarcity of FER datasets, Illumination, Face pose, Occlusion, Aging, and low resolution [8].

II. FEATURE EXTRACTION TECHNIQUE

The primary objective of this study is to investigate and evaluate various feature extraction techniques used in facial expression recognition systems. Through the investigation and comparison of various feature extraction techniques, this study seeks to shed light on their efficacy, strengths, limitations, and impact on the overall performance of facial expression recognition systems. There are two main categories of feature extraction techniques in the field of facial expression recognition: handcrafted methods and deep learning-based approaches[10]. Techniques for feature extraction for FER are shown in Figure 1.

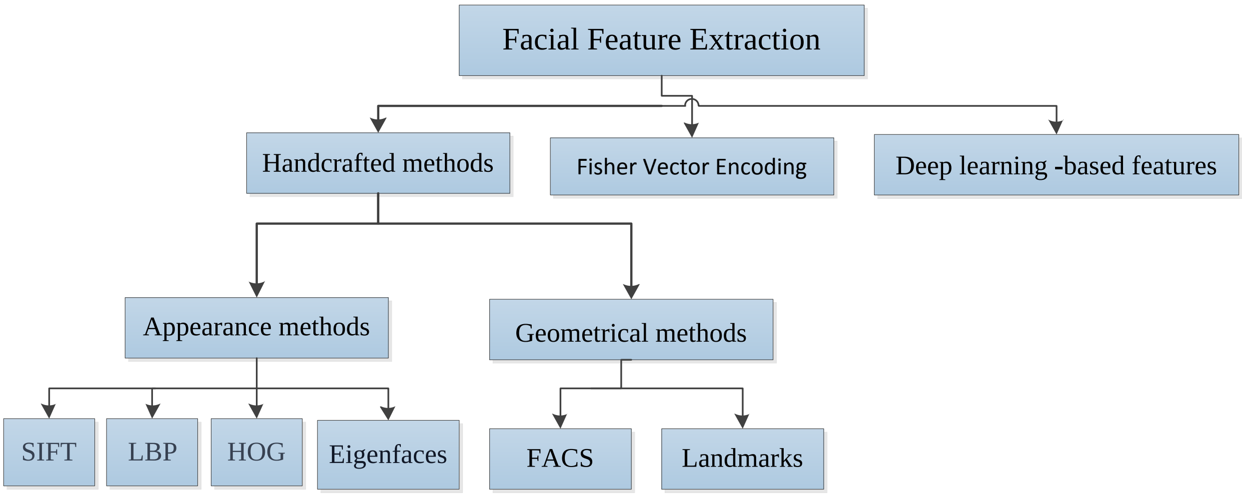

Fig 1. illustrates feature extraction methods for FER.

1- Handcrafted methods

Handcrafted feature extraction is the process of manually devising and selecting features from raw data to represent and capture pertinent information for a given task or problem. These features are engineered by human experts based on domain knowledge and understanding of the problem domain. Handcrafted feature extraction methods have been widely used in various fields such as computer vision, natural language processing, signal processing, and more [11].

When you have a limited amount of data and want to create a model without sacrificing significant or pertinent information, manually extracted features are crucial. The methods of handcrafted feature extraction involve the design of specific algorithms to extract discriminative facial features [12]. Two distinct kinds can be identified appearance- and geometric-based feature-based methods

A. Appearance Feature-Based Methods

The face's appearance alterations, such as creases, bulges, and furrows, are represented by appearance features. These characteristics permit the separation of diverse information sources, such as facial illumination and deformation changes, and can be implemented more automatically. They are less susceptible to interference, but frequently encounter complex computational issues and have a limited capacity to extract exhaustive and abstract features. Facial expression recognition accuracy is affected by dimensionality reduction techniques because the effects of the approaches are time-consuming and the characteristic dimension is tremendous [13]. There are a variety of prevalent techniques when it comes to methods based on appearance characteristics. Table 1 emphasizes the significance of the main distinctions between various feature extraction techniques in FER:

Table 1. Comparison of FER appearance feature extraction techniques

Feature Extraction Method	SIFT [14]	HOG [15]	Eigenfaces [16]	LBP [17]
Type	Local Feature-based	Shape-based	Appearance-based	Texture-based
Key Idea	Extract distinctive local	Compute gradients of	Represent facial	Describe texture patterns

	features based on key points and their descriptors	image intensities to capture local shape information	expressions as linear combinations of eigenfaces to capture main variations	according to local binary comparisons.
Computational Efficiency	Computationally intensive due to key point detection and descriptor extraction	Moderate efficiency, requires gradient computation and histogram construction	Moderately efficient, requires eigenface computation and projection	Moderate efficiency; local binary comparisons and histogram construction are required.
Adaptability to Lighting Conditions	Robust to some extent due to the extraction of local features	Sensitive to variations in illumination; may necessitate preprocessing or normalization	Sensitive to variations in illumination; may necessitate preprocessing or normalization.	Sensitive to variations in illumination; preprocessing or normalization may be required.
Dimensionality	High-dimensional feature representation	High-dimensional feature representation	Low-dimensional feature representation	Low-dimensional feature representation
Discriminatory Abil ity	Excellent discrimination for capturing distinctive local characteristics	Excellent for capturing shape-related characteristics including margins and contours	Excellent for depicting global appearance and facial variations	Excellent at depicting texture variations and patterns

B. Geometric Feature-Based Methods

geometrical attributes are Facial landmarks used to estimate the location of various facial image components, such as the eyebrows, jaw, and nostrils. Distances, curvatures, and other geometric properties can be used to represent the geometric facial attributes. Geometric feature can reduce computation time, but precise selection of feature points is required and they may not accurately capture subtle facial expression changes [18]. The extraction of geometric features requires the accurate selection of facial feature points, which can be challenging in cases of low image quality or complex backgrounds. In addition, these methods capture only changes in the overall facial contour while disregarding other relevant information, such as variations in skin texture, resulting in a diminished ability to detect subtle changes in facial expression [3]. Here are some common geometric feature-based methodologies employed in FER:

- Facial landmarks, also known as facial key points or landmarks, are specific points on the face that correspond to distinct facial features, such as the eyes, nose, mouth, and eyebrows. These landmarks provide valuable information about the facial geometry and can be leveraged for feature extraction in facial expression recognition systems. This section explores the utilization of facial landmarks for extracting discriminative features and discusses facial landmark detection algorithms and techniques [19]. Common methods for facial landmark localization include Active Shape Models (ASM), Active Appearance Models (AAM), and Constrained Local Models (CLM) [20]. Advantages of utilizing facial landmarks for feature extraction include robustness to changes in lighting conditions, pose, and image resolution. Limitations, such as sensitivity to facial occlusions, accuracy of landmark detection, and robustness to variations in facial expressions [19].

- Facial Action Coding System (FACS) is a widely used instrument for objectively describing facial expressions, developed in the 1970s. It has been applied in various disciplines, including emotion recognition, lie detection, character animation, facial recognition technology, and clinical assessments of facial muscle dysfunction or asymmetry. FACS dissects facial expressions into distinct components called action units (AUs), which represent distinct facial muscle movements or combinations of facial muscle movements [21]. Each AU represents a distinct facial muscle movement or combination of facial muscle movements, which may occur independently or in conjunction with other AUs. The FACS manual provides a comprehensive description of each AU, including its associated muscle contractions, anatomical basis, and observable facial changes. By observing and codifying these action units, researchers can objectively measure and analyze facial expressions across individuals, cultures, and emotional contexts. FACS defines all potential motions in 44 unique AUs, which are separated into three categories: facial musculature (AUs that characterize the upper and lower face), eye positions, and head movements [22].

Table 2. Comparison of the Facial Action Coding System (FACS) with facial landmarks [23]:

Aspect	Facial Action Coding System (FACS)	Facial Landmarks
Purpose	Describing and quantifying facial movements by means of muscle contractions	Representing precise coordinates on the visage for measuring geometric changes
Methodology	Coding and annotation of action units manually based on muscle activations.	Automatic monitoring and detection based on computer vision techniques

Expertise Requirement	Requires specialist FACS coding knowledge and training.	Requires expertise in computer vision for landmark detection and monitoring
Information Captured	Muscle activations and intensity associated with facial expressions	Geometric alterations and facial movements
Output	Detailed account of muscle contractions and their contributions to facial expressions.	Positional details of particular facial points
Relationship	FACS analysis can use facial landmarks as inputs to quantify action units.	In FACS, facial landmarks are the premise for measuring geometric alterations and movement.

2. Deep Learning-Based Methods

Deep learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in a variety of computer vision tasks, including facial expression recognition. CNNs are able to autonomously acquire pertinent features directly from the raw pixel data, eradicating the need for manually designed features [10]. Deep learning-based facial recognition systems use the entire face image as input, focusing on specific facial features like eyes, nostrils, and mouth. This can lead to loss of vital information and irrational outcomes. Insufficient data in facial expression recognition databases and limitations in single-task CNN networks can cause overfitting. Convolutional neural networks, unlike manual feature extraction, can independently learn image features and acquire more features, sharing the weight with neural networks. However, they also have drawbacks, particularly in fitting [24].

The comparison of handcrafted and CNN-based feature extraction methods considers classification accuracy, computational resources, and robustness to noise.

(a) Classification Accuracy:

Handcrafted methods show reasonable performance in facial expression recognition tasks but struggle to capture complex patterns. CNN-based methods, like convolutional neural networks, improve performance in computer vision tasks by capturing complex facial expressions with high accuracy. Combining these methods leads to better classification results [25].

b) Computational Resources (Required Time):

Typically, handcrafted methods have lower computational requirements than CNN-based methods. These methods frequently involve straightforward calculations and local operations, allowing them to be executed more rapidly, while CNN-based methods may require more time and computational resources during the training phase but offer faster inference during testing [26].

(c) Noise Resistance:

Manual Methods Manual methods are susceptible to noise and illumination variations in facial images. Eigenfaces may grapple with variations in pose or facial occlusions, whereas LBP and HOG may be affected by changes in illumination. CNN-based Methods CNN-based methods are renowned for their resistance to image disturbance and variation. CNNs' convolutional layers can extract features that are invariant to certain types of noise, allowing for improved generalization and robustness to variations in illumination conditions, pose, and occlusions [27].

In conclusion, CNN-based methods outperform handcrafted methods in classification precision, especially for complex facial expressions. Handcrafted methods have reduced computational requirements, but CNN-based methods provide efficient inference and noise-resistance. It is essential to note that the specific efficacy and trade-offs can vary based on the dataset, network architecture, and implementation details. Therefore, it is recommended to conduct experiments and evaluations on the particular scenario and dataset of interest in order to make well-informed decisions regarding feature extraction techniques.

3. Fisher Vector Encoding (FVE)

FVE is not a method for extracting features but rather for encoding and representing them [28]. It is a technique for encoding features that is compatible with both handcrafted methods and deep learning techniques. In the context of facial expression analysis, Fisher Vector encoding can be applied to handcrafted features, including local binary patterns (LBP), histogram-based features, and geometric features, to generate a more condensed and descriptive representation of the extracted features. This encoding method aids in capturing facial expressions' characteristic patterns within the feature space. Conversely, Fisher Vector encoding can also be utilized in tandem with deep learning techniques. Deep learning models, such as convolutional neural networks (CNNs), are used to extract high-level features from facial images, and Fisher Vector encoding is then applied to generate a more condensed and discriminative representation of these features [29]. Vector encoding is a method for FER that has garnered increasing interest from the affective community. Using Fisher vectors, this method encodes improved dense trajectory and geometric features, which can then be classified using a variety of methods. [30].

III. THE PROPOSED MODEL

To implement the facial expression recognition system with the three phases (Preprocessing, Feature Extraction, and Classification), we'll create a method that takes the input image and returns the predicted facial expression. Figure 2 clarifies the phases of the proposed system for facial expression recognition.

ISSN: 2710-2165

3.1 Pre-processing

In facial expression recognition systems, preprocessing is essential in preparing facial images for feature extraction[31]. The preprocessing stages, namely converting the images to grayscale, applying histogram equalization, and resizing them to a standard resolution, are described in greater depth below.

Convert the facial images to grayscale: Converting facial images to grayscale involves transforming the images from their native RGB (Red, Green, and blue) color space to a grayscale color space. This conversion facilitates the ensuing feature extraction procedure by reducing the data's dimension. It eliminates color information that may not be necessary for facial expression recognition and focuses solely on variations in the intensity of facial features [32]

Histogram equalization: is a technique used to increase the contrast and overall quality of grayscale facial images. It redistributes the intensity values of the image's pixels to make more efficient use of the dynamic range. By elongating the intensity histogram, histogram equalization improves the visibility of facial features and helps to compensate for varying illumination conditions. This preprocessing phase improves the discriminative power of subsequent feature extraction methods by bringing out more prominent facial features and enhancing the distinction between various facial expressions [33].

Resized: To ensure uniform input across the dataset, facial expression recognition requires images resized to a common resolution of 20 x 20 pixels. This ensures accurate and consistent feature extraction, reducing computational complexity and memory requirements. Standardizing image size also improves comparability and generalizability of the facial expression recognition system across diverse datasets and testing scenarios. By retaining the aspect ratio and occupying the same space in each image, facial expression recognition improves overall accuracy and generalizability [34].

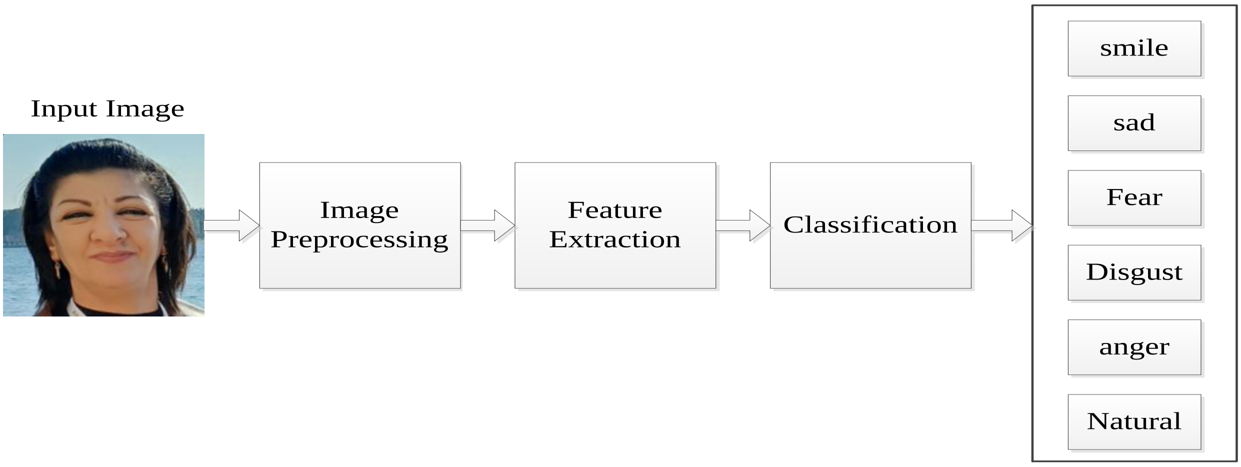

Fig 2. depicts the proposed FER system

3.2 Feature Extraction

A novel method for FER is proposed that combines deep learning, PCA, and GLCM. PCA captures the essential variations and reduces disturbances in the data. GLCM is a texture analysis method that calculates the spatial relationships between adjacent pixels in an image, thus disclosing texture properties. Combining PCA and GLCM as feature extraction techniques enables the 1D-CNN model to exploit a reduced feature space with meaningful representations that capture relevant facial expression characteristics and texture information. the proposed method seeks to improve the accuracy and robustness of FER systems.

3.3 Classification

The classification of facial expressions using a 1D-CNN (1-Dimensional Convolutional Neural Network) is an efficient method. The architecture of a 1D-CNN for facial expression recognition is composed of layers that sequentially analyze the fused features obtained in the preceding stages. These layers execute convolutional operations on the input features to derive spatially pertinent data. Each convolutional layer employs a series of filters with distinct kernel sizes to capture distinct feature levels. Output Layer: The output layer consists of neurons equal to the number of classes (facial expressions) and employs a suitable activation function (Softmax) to generate the probability distribution over the classes. Figure 3 shows Typical architecture layers:

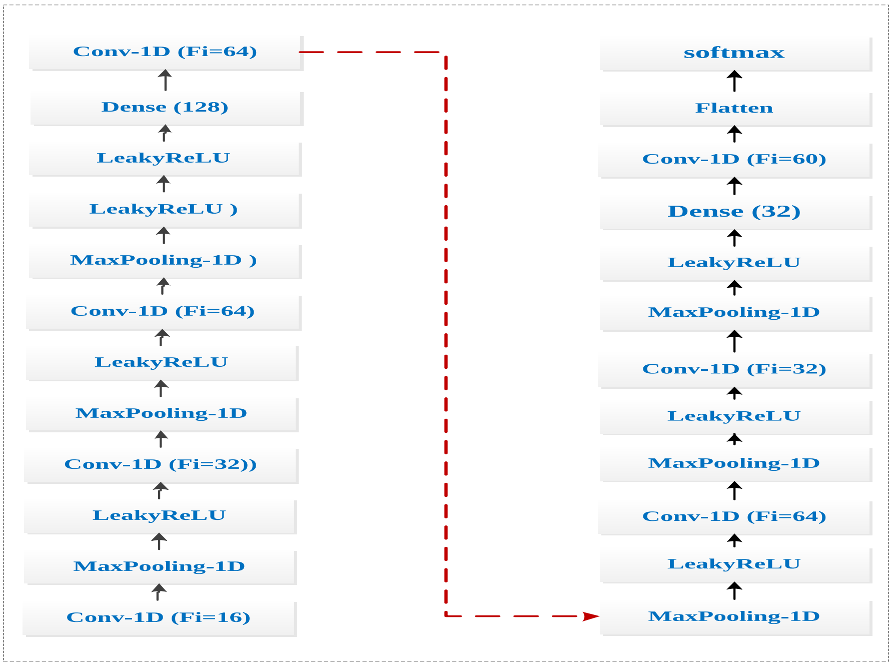

Fig 3. details the layers.

IV. Experimental Results

Data Set: The dataset utilized in this research comprises 70 images facial expressions obtained from real-life scenarios. These expressions encompass a range of emotions, including joy and neutrality. Ethical considerations were carefully observed during the data collection process to adhere to privacy guidelines and protocols. The dataset is then split into a 70:30 ratio, with 70% of the data allocated for training and the remaining 30% for testing the model.

Prepressing: Figure 4 depicts a sample of the outcomes of the preprocessing stage for the collected data set. Converting an image to grayscale facilitates post-analysis and image processing by reducing the dimensionality of the data and emphasizing structural differences and intensities as opposed to color information. In recognizing facial expressions, color information is not essential and can be effectively captured using only grayscale images. Histogram equalization is a technique commonly employed in FER to enhance the contrast and overall quality of grayscale facial images. It is used as a preparatory phase prior to feature extraction to enhance the visibility of facial features and compensate for varying illumination conditions. To preserve uniformity and facilitate analysis, all images in the dataset were resized to a resolution of 20 x 20 pixels. This assures image size uniformity and simplifies the extraction of image features. One of the processing procedures that reduces a huge dataset into a smaller one is feature extraction [35]

Fig. 4 Phase of preprocessing a) original facial expression images; b) grey scale results; c) histogram equalization results; and d) resizing results.

The 1D-CNN model demonstrated exceptional performance in facial expression recognition, achieving a remarkable accuracy score of 99.99% on various evaluation metrics, including accuracy, precision, recall, and F1-score. It was tested on more than one data set and achieved the same results. This outstanding accuracy highlights the model's robustness and reliability in real-world scenarios, outperforming existing models. The success can be attributed to the precise selection of extracted features from PCA, GLCM, and CNN, as well as the well-chosen 1D-CNN architecture. Before training the proposed 1D-CNN model, specific parameters were defined, which are outlined in Table 3. The model's performance is visually represented in Figure 5.

Table 3. The parameters employed in the training phase

parameters	value
Epochs	200
Optimizer	Adam
Batch size	64
Learning rate	0.001

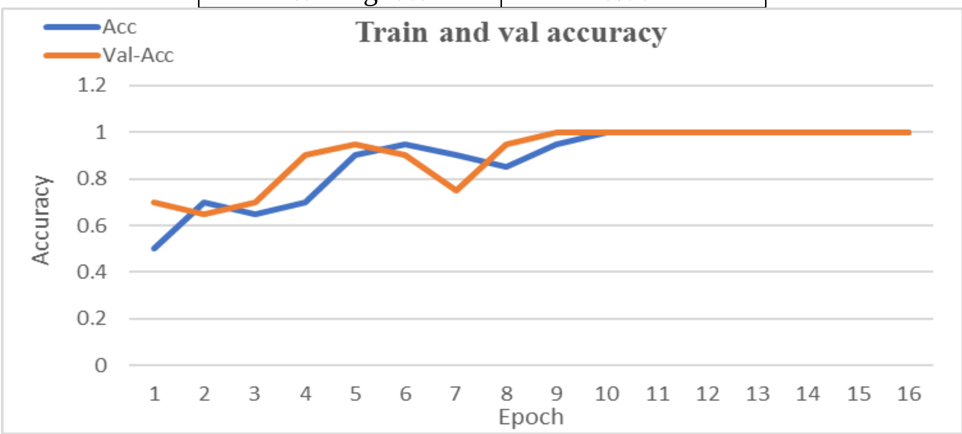

Fig 5. depicts the performance of the 1D-CNN model

V. CONCLUSION

In conclusion, this study presented a comprehensive evaluation of feature extraction techniques in facial expression recognition, highlighting the strengths and limitations of each method and their impact on system performance. The proposed approach, which integrated deep learning, PCA, and GLCM, achieved an outstanding 99.99% accuracy score using a 1D-CNN model. The results demonstrated that PCA and GLCM significantly improved the discriminative power of extracted features by capturing essential spatial and textural information from facial images. This integration led to highly accurate recognition of facial expressions and showcased the potential of combining different techniques for enhanced performance. This research serves as a foundation for further advancements in facial expression recognition. By continually exploring new feature extraction techniques, validating their performance on diverse datasets, and optimizing for real-world applicability, we can pave the way for more robust and effective facial expression recognition systems in fields like human-computer interaction, emotion analysis, and beyond.

ACKNOWLEDGMENT

The authors would like to thank the College of Engineering, Al-Iraqia University**.**

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