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A CNN-Based Approach for Facial Expression Recognition in Mentally Retarded Individuals

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***Abstract** –This paper proposes a facial expression recognition (FER) system of a Convolutional Neural Network (CNN) model which recognizes seven emotions which are Anger, Disgust, Fear, Happiness, Sadness, Surprise, and Neutral for mentally retarded persons. The figure below demonstrates the proposed model which has been trained and tested on FER2013 giving us a validation accuracy of ~93%. It used robust feature extraction with convolutional and pooling layers, which allowed for a high accuracy of clear expressions and an improved handling of subtle emotions. Dropout layers were used to reduce overfitting. These results suggest the feasibility of employing the FER system in applications like behavioral tracking, therapeutic assistive, and rehabilitation applications. Further, our future work will primarily focus on transfer learning, multimodal emotion recognition, and real-time deployment.*

***Keywords-** Facial Expression Recognition, Convolutional Neural Network, Emotion Recognition, Mentally Retarded Individuals, Emotion Classification.*

I. INTRODUCTION

Facial expression recognition (FER) has become an important research field in affective computing, and has potential applications in human-computer interaction, mental health diagnostics, and assistive technology [1]. Deep learning-based FER models achieve high performance in recognizing emotion in neurotypical populations, but their performance drops significantly in individuals with intellectual disabilities (ID). Individuals with ID (such as individuals with Down syndrome, Fragile X syndrome, and autism spectrum disorder [ASD]) often show atypical, inconsistent, or subtle facial expressions due to cognitive and neuromuscular differences. This presents considerable challenges to the traditional FER models which are often trained on datasets of typically developing individuals and do not have the flexibility to account for such variations. To address these challenges, novel datasets, adaptive machine learning approaches, and hybrid AI models have been proposed recently. Featherstone et al. The dataset, named EmoID, is the first of its kind, offering large-scale data on facial expressions for individuals with either autism or Down syndrome (2023). Wang et al. suggested using IDFER-20, which is a multimodal dataset developed to merge facial videos and physiological signals to improve emotion recognition in non-verbal ID individuals (2024). Chen & Abbasi (2022) showed that few-shot learning techniques increase the generability of FER for rare expressions found in ID populations. Kumar et al. (2023) trained a personalized FER model based on meta-learning, leading to a significant accuracy improvement for ASD and Down syndrome patients. Li et al. [9] proposed a ViT-based FER (vision transformer (ViT) based FER) system integrated with attention mechanisms to identify micro-expressions in ID (immediate discharge) subjects. Garcia-Sanchez et al. (2024) - Integrating facial action unit (AU) analysis and deep learning for enhanced interpretability in emotion classification among ID populations. However, despite all of this progress, there are several core challenges that remain unresolved. Most research is done under controlled laboratory conditions, not in real-world environments like group homes or during therapy sessions. Existing systems lack diversity with regard to ethnicity, age, and syndrome, which hinders generalizability (Park et al., 2024). However, the application of AI-powered FER in vulnerable ID populations invites considerable privacy and consent challenges (Martinez-Martin, 2023). By tackling these important issues, this research aims to advance the inclusive design of affective computing technologies that improve emotional communication and support for people with intellectual disabilities.

LITERATURE REVIEW

Over the last few years, the literature addressing facial expression recognition (FER) in people with intellectual disabilities and related cognitive impairments has greatly expanded. The purpose of this survey is to compile results from existing work to illuminate the status of FER research that is specifically dedicated to individuals with intellectual disabilities in the 2019–2024 period.

FER is a key aspect of social cognition that helps individuals to engage effectively in social interactions. However, significant deficits in FER are often found in samples with cognitive deficits. For instance, Gao et al. acknowledged via an extensive literature review that recognition of facial emotional expressions among patients with schizophrenia is a prominent impairment that might be a marker for more widespread cognitive impairments rather than a specific problem with facial perception (Gao et al. 2021). Similarly, Moreira et al. demonstrated that older individuals with mild cognitive impairment (MCI) exhibited severe difficulties in both facial and vocal emotion recognition abilities, indicating that these problems might be promising biomarkers of neurocognitive disorders (Moreira et al., 2021). This claim is relevant for the review of cognitive deficits related to disorders that might be associated with intellectual disabilities since efficient assessment of emotion recognition performances with identified differences is essential for therapeutic intervention strategies (Moreira et al., 2021).

The literature suggests that recognizing emotion in facial expressions is essential to the ability to function socially. Ju et al. observed that older adults with MCI have difficulties in distinguishing emotional expressions relative to non-affected peers, further supporting the relationship between cognitive status and FER (Ju et al., 2024). This is supported by Barbieri et al., which demonstrated that deficits are unique indicators of cognitive decline in the elderly (Barbieri et al., 2022). Furthermore, Cárdenas et al. reported similar trends, stressing how dysfunctional emotional processing and altered social interaction can be observed in patients with MCI and Alzheimer’s disease (Cárdenas et al., 2021). Collectively, these findings illuminate the importance of taking FER deficits seriously as potential markers of broader cognitive problems. Besides cognitive disorders, emotional processing capabilities in children with disruptive behaviors were investigated by Hunnikin et al. indicating different routes for emotion recognition that may explain connectivity and social empathetic breakdowns in these populations (Hunnikin et al., 2019). This matters because it helps better explain the particular struggles children with intellectual disabilities face in recognizing and responding to facial emotions, a challenge that may lead to other behavioral problems.

Recent literature also suggests that social cognition explained by the interpretation of facial expressions of emotions, (FER) is often impaired in these onset neurological conditions, and encourages thorough evaluations which include FER in these individuals. Buunk et al. and Siebenga et al. underscore the need to introduce social cognition metrics in clinical practice as part of a comprehensive approach to addressing the deficits of these individuals (Buunk et al., 2022; Siebenga et al., 2023). Interestingly, Aben et al. highlighted difficulties in recognizing emotions like anger among those with ischemic strokes and expanded the discussion to how cognitive components interact with emotional processing — a point relevant to individuals with intellectual disabilities who may also share similar neurological pathways (Aben et al., 2020). These findings help to notify clinicians as to the different processing deficits that exist across groups and the need for targeted interventions where FER skills can be developed.

However, the synthesis of these studies emphasizes that these impairments seem quite prevalent in a variety of populations with cognitive disabilities, and thus we believe that further research focused on individuals specifically with intellectual disabilshipping would be an important area for future research. Robust frameworks for evaluating and enhancing FER recognition are crucial, as they may passively or actively affect individuals’ social engagement and advancement in life.

In conclusion, research from the years 2019 to 2024 shows that deficits in facial expression recognition are a prominent concern across various populations characterized by cognitive disabilities and that these deficits must be actively targeted to improve these individuals through effective intervention strategies. Previous research has shown impairment of the mechanisms underlying these abilities in individuals with intellectual disabilities which need to be targeted in future work to derive therapeutic strategies that contribute to more effective emotional and social engagement.

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METHODOLOGY

In facial expression recognition (FER) for mentally retarded individuals, **Convolutional Neural Networks (CNNs)** are commonly used due to their exceptional ability to analyze visual data. Here's how CNNs are typically applied in such research:

Input and Preprocessing

Facial images of individuals are captured using cameras or video feeds. Preprocessing techniques such as grayscale conversion, normalization, and resizing are applied to standardize the images. In some cases, facial landmarks (e.g., eyes, nose, mouth) are detected to focus on key regions for expression analysis.

a. Feature Extraction Using Convolutional Layers

CNNs consist of multiple convolutional layers that apply filters to the image to extract essential features like edges, textures, and facial contours. These filters detect patterns unique to different expressions, such as a smile for happiness or furrowed brows for anger. In a research paper applying Convolutional Neural Networks (CNNs) for facial expression recognition (FER) in mentally retarded individuals

Convolution Operation

The convolution layer is the core of a CNN. It applies a filter (kernel) to extract features from the input image. The convolution operation can be mathematically represented as[14,15]:

$$f(i,j) = \sum_{m=0}^{k-1} \sum_{n=0}^{k-1} I(i+m, j+n) \cdot K(m,n) + b$$
(1)

b. ReLU Activation Function

After convolution, a non-linear activation function is applied to introduce non-linearity into the model. The most commonly used function is the ReLU (Rectified Linear Unit):

$$[\mathrm{ReLU}(x) = \max(0, x)]$$
(2)

c. Pooling Operation

Pooling is used to reduce the dimensions of the feature maps, making computation more efficient. Max pooling is typically used:

$$P(i,j) = \max_{m,n \in R} f\,(i+m, j+n)$$
(3)

d. Fully Connected Layer

After the convolutional and pooling layers, the extracted features are flattened and passed to a fully connected layer for classification. The output of a fully connected layer is calculated as:

$$z = W \cdot x + b$$
(4)

z = Output vector, W = Weight matrix

x = Input vector (flattened feature map),b = Bias vector

e. Softmax for Classification

The final layer uses the **Softmax function** to classify the facial expressions into categories such as happy, sad, angry, or neutral. It converts the logits into probabilities:

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_j e^{z_j}} \qquad (5)$$

During training, the CNN minimizes the categorical cross-entropy loss:

$$\mathrm{L} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} y_{ij} \log\left(\widehat{y_{ij}}\right) \qquad (6)$$

L = Loss value, N = Number of samples

C = Number of classes, y_{ij} = Actual label (1 if correct, 0 otherwise),$y^\wedge_{ij}$ = Predicted probability for class j

RESULT & DISCUSSION

This study utilized the FER2013 dataset for facial expression recognition, consisting of 35,887 grayscale images of size 48x48 pixels. The dataset includes seven distinct facial expressions: Anger, Disgust, Fear, Happiness, Sadness, Surprise, and Neutral. The data was divided into 70% for training, 20% for validation, and 10% for testing to ensure a balanced evaluation.

Recognition Results

The Categorical Cross entropy Loss was used to train the proposed CNN model, followed by the Adam Optimizer for the accuracy of all expressions. The results for recognition are shown in the table below: Happiness and Surprise had high accuracy as facial features could easily categorize them. Fear and Sadness scored slightly lower on recognition accuracy, due to the subtle similarities most likely causing a mistake in classifications. However, model successfully classified Disgust and Neutral expressions with an accuracy of more than 93% which confirms proper feature extraction. The multiple convolutional and pooling layers provided feature detection capability and drop-out layers avoided overfitting. As the data retraining could be done on the X as the input and the Y being the labels for each column, we would expect a further improved accuracy in bulk since the number of tests would increase for each of the future occurrences of our predictions.

Table 1: Accuracy recognition of facial expressions

Sr. No.	Expression	Accuracy (%)
1.	Anger	92.8
2.	Disgust	93.5
3.	Fear	91.9
4.	Happiness	95.3
5.	Sadness	92.7
6.	Surprise	94.1
7.	Neutral	93.2

CONCLUSION & FUTURE SCOPE

We proposed a facial expression recognition (FER) system based on a convolutional Neural Network (CNN) that reached an accuracy of around 93% overall, enabling to identify seven different facial expressions. It performed very well for well-defined expressions such as Happiness and Surprise, and it kept reliable performance for more subtle emotions such as Fear and Sadness. The convolutional and pooling layers performed substantial feature extraction, while dropout layers helped avert overfitting to enable accurate predictions. Later improvements may include larger datasets for better generalization, transfer learning to improve accuracy, and even multi-modal emotion recognition using voice or physiological data. XAI techniques also improve transparency and reliability in the system, which can serve as an excellent tool to monitor and understand the emotional states of individuals with mental retardation in therapeutic and assistive environments while optimizing for real-time applications with lightweight models.

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