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Facial Expression Analysis: A Review of Image Processing Approaches and Its Implications for Mental Health Assessment

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Abstract: Facial expressions are very crucial when conveying emotions and mental states, making them valuable indicators for assessing an individual's mental health. This review paper analyses into the diverse approaches utilized in facial expression analysis, offering a comprehensive examination of the methodologies employed to analyze facial expressions in the context of mental health assessment. To highlight the significance of non-verbal cues in understanding various mental health conditions Firstly, the relationship between facial expressions and mental health is explored. The use of the different techniques for face expression analysis is then highlighted in an overview that includes feature extraction, classification algorithms, and machine learning techniques. The paper also examines the utilization of facial expression analysis (FEA) in mental health assessment. Along with possible future study areas and technological developments, challenges like cultural diversity and variety in facial expressions are addressed. Different potential approaches are highlighted in this paper to improve the assessment of mental health by analysing facial expressions, providing data that is valuable for future research and real-world applications

Keywords: Mental Health, Facial Expression, Image Processing, Non-Verbal Cue, Health Assessment.

INTRODUCTION

Facial expressions are “The facial changes in response to a person’s internal emotional states, intentions, or social communications”. They are the window to human emotions which reflect the mental state and psychological well-being of a person. Understanding human emotions through facial expressions is necessary for being emphatic, have effective communication and for the mental well-being of the person. Therefore, facial expression analysis refers to computer programs that use visual data to identify and analyze changes in facial features and motion. Image processing allows important information about emotional states and mental health to be extracted from facq azial expressions. Paul Ekman's cross-cultural studies in the 1960s and 1970s identified six basic emotions (Happiness, Sadness, Surprise, Fear, Anger, Disgust) with corresponding universal facial expressions as shown in the figure 1.

Fig 1: Different facial expressions for basic emotions [1]

Recognizing these emotions in others helps us to empathize and respond properly and mirroring certain emotions like returning a smile helps strengthen social connections. However there are certain challenges that are encountered in facial expression recognition .Human faces can exhibit a plethora of expressions that range from subtle expressions to overtly emotional states, hence capturing this variation in expressions is challenging due to differences in light, pose, occlusions and individual idiosyncrasies. For efficient communication, these complex facial muscle movements that represent underlying psychological states are necessary [2]. Image processing, on the other hand, refers to the alteration and analysis of digital images using various methods and techniques. Image processing allows important information about emotional states and mental health to be extracted from facial express ksions [3]. Since facial expressions can reveal emotional disorders and act as indicators of psychological discomfort, they are essential in the assessment of mental health. For example, depressed peoplemay have a flattened effect and less expressive facial expressions, whereas anxious people may show more tension and fear in their facial expressions. The sensitivity of mental health assessments can be improved by image processing algorithms, which can identify minute variations in facial expressions that would not be visible to the human eye[4].By analyzing these small indicators in facial expressions, image-processing tools let researchers and physicians measure

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mental health more accurately [5,6]. But there are disadvantages to this strategy as well. For example, biases or mistakes in FEA algorithms may result in incorrect interpretations of emotional states [7].

FEA for mental health assessment via image processing uses several existing approaches. These include more sophisticated techniques that make use of ML and deep learning (DL) algorithms, as well as more conventional techniques like facial feature recognition and categorization [8,9]. Conventional techniques frequently depend on manually drawn characteristics and may have trouble capturing individual differences in facial emotions. ML algorithms, on the other hand, can automatically extract discriminative features from data, hence enhancing the precision and resilience of FEA. These methods, however, could be computationally demanding and need big datasets for training [10].

This paper examines various image processing approaches used in FEA, highlighting their advantages and disadvantages in interpreting the nuances of facial expressions. The integration of image processing with FEA holds promise for advancing mental health assessment, potentially revolutionizing diagnostic and therapeutic interventions for individuals with psychological disorders.

RELATIONSHIP BETWEEN FACIAL EXPRESSIONS AND MENTAL HEALTH

A core component of non-verbal communication are Facial Expressions, offering a direct and immediate reflection of a person's emotions, attitudes, and mental state. They serve as visible indicators of emotional health and play a vital role in how individuals express, perceive, and regulate emotions. The capacity to recognize and react to these expressions is essential to effective emotion management.

Facial expressions are crucial for identifying and assessing mental health issues in clinical settings. Clinicians often rely on observable behavioural cues to assess a patient's mental state, symptom severity, and treatment progress [11]. For instance, persistent frowning or grimacing may indicate anxiety or distress, while reduced facial expressiveness (flattened affect) is commonly associated with conditions such as schizophrenia [12,13].

Facial expressions also underpin social interaction and relationship-building. The ability to accurately recognize and respond to emotional cues is crucial for empathy and effective communication. Impairments in this ability, as seen in autism spectrum disorder (ASD), can significantly affect social functioning [14–16].

Additionally, facial expressions can signal stress and coping capacity. Individuals experiencing trauma or chronic stress may exhibit tense expressions, whereas those with better adaptability often display more relaxed and open facial cues. Analysing these patterns can support interventions aimed at improving psychological resilience and overall well-being [17].

Overall, because facial expressions offer important insights into emotional states, social functioning, and mental health conditions like anxiety, depression, and schizophrenia, they are crucial for both diagnosis and therapeutic intervention.

IMAGE PROCESSING TECHNIQUES FOR FEA IN MENTAL HEALTH ASSESSMENT

Facial Expression Analysis (FEA) is a key tool in mental health assessment, enabling the identification of emotional states and psychological conditions through facial cues. Variations such as reduced expressiveness or atypical emotional displays can indicate disorders like schizophrenia, anxiety, or depression. FEA uses image-processing techniques, such as feature extraction, classification algorithms, and machine learning techniques, to achieve accurate analysis. These methods facilitate better clinical results, individualized treatment planning, and early detection.

Feature Extractio

Feature extraction is a critical step in Facial Expression Recognition (FER), focusing on identifying key facial characteristics that signal emotional states. It generally involves two approaches: geometric-based and appearance-based methods.

Geometric feature-based methods:

These methods analyse the spatial relationships (distances and angles) between prominent facial features such as the eyebrows, eyes, nose, and mouth to capture structural changes in expressions (Fig. 2) [18].

Techniques like the Local Curvelet Transform (LCT) are used to extract geometric descriptors, including mean, entropy, and standard deviation [19].

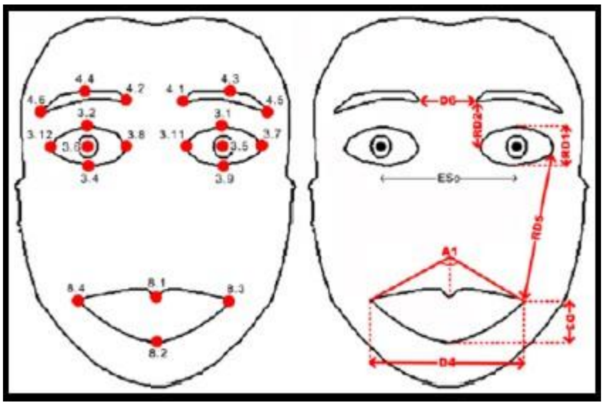

Fig 2: Landmark features [18]

Appearance-based methods:

These methods focus on the texture and visual appearance of facial features to capture emotional variations. Common descriptors include Local Binary Pattern (LBP), which captures local texture and edge information; Histogram of Oriented Gradients (HOG), which represents shape and edge directions; and Gabor filters, which extract texture using magnitude and phase information [19,20,22]. Other techniques such as Gaussian Laguerre (GL) and Vertical Time Backward (VTB) descriptors capture both texture and shape-related features of facial components [21].

In addition, machine learning approaches like the Supervised Descent Method (SDM) are used to classify facial expressions and detect patterns associated with mental health conditions, while improved variants such as Weighted Projection-Based LBP (WPLBP) enhance feature extraction and classification performance [23,24].

Together, these techniques enable automated systems for early detection, screening, and monitoring of mental health disorders, supporting more effective interventions and treatment strategies.

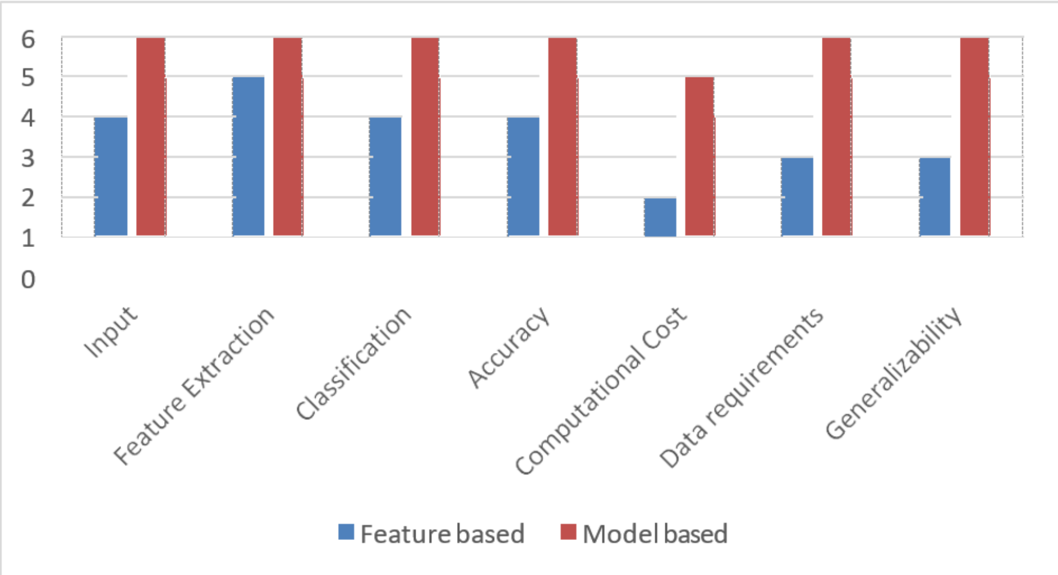

Fig 3: Graphical comparison of feature based and model based approaches

The above figure shows the graphical representation comparing feature-based and model-based approaches for Facial Expression Recognition . Each aspect is rated on a scale of 1 to 5, with higher values representing stronger performance. In summary, feature-based approaches rely on specific facial landmarks and geometric information, while model-based approaches involve building comprehensive models that represent the entire face's structure and dynamics, including deep learning methods. The choice between the two depends on the available data, computational resources, and the desired accuracy level.

Classification Algorithms

Classification algorithms play a crucial role in Facial Expression Analysis (FEA) by categorizing facial expressions into predefined emotion classes using extracted features. These methods learn decision boundaries and, in some cases, map features into higher-dimensional spaces to improve class separability.

Common classifiers include Naïve Bayes (NB), which is simple and fast but assumes feature independence [25]; Multilayer Perceptron (MLP), capable of learning complex non-linear patterns but requiring large datasets and computational power [26]; and Decision Trees (DT), which are easy to interpret but prone to overfitting [27].

Instance-based methods like K-Nearest Neighbour (KNN) are intuitive and require no training, though they are computationally expensive [28]. Support Vector Machines (SVM) are effective in high-dimensional spaces and handle both linear and non-linear data well, but can be costly for large datasets [29]. Ensemble methods such as Random Forests reduce overfitting and handle high-dimensional data effectively, while Gradient Boosting Machines (GBM) provide high predictive accuracy by sequentially correcting errors, though they require careful tuning and longer training times [28,30].

Overall, each algorithm offers specific strengths and limitations, and the choice depends on dataset size, complexity, and application requirements.

ANALYSIS OF MENTAL HEALTH ASSESSMENT

To understand mental health conditions and to improve diagnosis ,the datasets used and the deep learning approaches used are analysed**.** Table 1 includes references [31] to[40].

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Table 1: Analysis of datasets

Year	Author	Dataset	Description	Mental Health Disorders
2022	Tlachac et.al	Student Suicidal Ideation and Depression Detection (Student SADD)	Voice memos and text replies captured with smartphone keyboards and microphones. It combines voice and text data for depression and suicide risk assessment.	Depression, Suicidal ideation,
2022	Shen et.al	Emotional Audio Textual Depression Corpus (EATD-Corpus)	Transcripts of text and audio from student interviews that were performed by a virtual interviewer using an application. Significance: Multimodal dataset combining textual and audio data, enabling study of both verbal and non-verbal cues related to depression.	Depression
2022	Urban et.al	Multi RedditDep dataset	Reddit photos uploaded by individuals who have at least one post in the depression community. Significance: Visual data from social media associated with depression.	Depression
2022	Mihov et.al	Psyche Net-G dataset	Incorporates user social activities, such as quote-tweets, mentions, and bidirectional replies, to expand the PsycheNet dataset. Significance: Studies depression in the context of social networks.	Depression
2021	Zhang et.al	Multi-modal Getty Image Depression and emotion (MGID) dataset	Getty Image textual and visual documents with an equal number of samples that are depressed and those that are not. Significance: Combines visual and textual data, providing a balanced set for studying depression indicators in media content.	Depression
2021	Pirayesh et.al	Psyche Net dataset	A dataset based on social contagion that includes the timelines of Twitter users and the people they are friends with both ways. Significance: Studies depression in the context of social networks.	Depression
2020	Vesel et.al	Bi Affect dataset	The dynamics of keyboard typing as recorded by a mobile application. Significance: Studies depression through typing patterns on mobile devices.	Depression
2020	Orton et.al	Well-being	Conversational interviews by a computer science researcher captured on video Significance: Provides visual data of natural conversations, allowing analysis of facial expressions and body language associated with anxiety and depression	Anxiety, Depression
2019	Cao et.al	Sina-Weibo suicidal dataset	Suicidal and controlling people's posts on Sina microblogs Significance: Provides data for studying suicidal tendencies through social media posts.	Suicidal ideation

2019	Rutter et.al	Fitbit Bring-Your Own- Device (BYOD) Project by the “All of Us” research program	Clinical evaluations, demographics, and Fitbit data (such as steps, calories, and active duration) Significance: Combines clinical data with wearable device data for mental health research.	Anxiety, Depression
2018	Cohan et.al	Self-Reported Mental Health Diagnosis Corpus (SMHD)	Tweets from users under control and those with one or more mental health disorders Significance: Comprehensive dataset covering a broad spectrum of mental health conditions, allowing for comparative studies.	Autism, bipolar disorder, schizophrenia, ADHD, borderline personality disorder, eating disorder, OCD, PTSD, anxiety, seasonal affective disorder, depression.

Future directions to evaluate mental health involves analyzing information collected over time by many authors which reveal important patterns, gaps in the field. Depression, anxiety, bipolar disorder, PTSD, schizophrenia, and other conditions are covered by the datasets that are gathered from several sources, including social media posts, interviews, and smartphone sensor data.

DL-BASED ANALYSIS

This section will examine many DL methods for mental health detection that have been proposed by different researchers to address current challenges in this area. Table 2 gives the performance of different DL approaches used to assess the different mental health conditions. Table 2 includes references [41] through [57].

Table 2: DL-based analysis

Author, Year	Technique Used	Aim	Performance
Matsubara et al., 2019	DFNN	Psychiatric illness diagnosis	Baseline ACC = 0.720, ACC = 0.766
Su et al., 2019	LSTM and Autoencoder	Prediction of mood disorder	Baseline ACC = 0.498, ACC = 0.692
Pinaya et al., 2019	Autoencoder	Identifying aberrant patterns in neuropsychiatric illnesses (ASD, schizophrenia)	Baseline ACC = 0.569–0.637, ACC = 0.639–0.707
Acharya et al., 2018	CNN	Prediction of depression	ACC = 0.960 (right hemisphere), ACC = 0.935 (left hemisphere)
Dawood et al., 2018	LSTM and CNN	Depression prediction	ACC = 0.901
Du et al., 2018	RNN and CNN	Determination of psychological stresses associated with suicide	Baseline ACC = 0.703, ACC = 0.72 (RNN); ACC = 0.74 (CNN)
Cong et al., 2018	LSTM	Depression prediction	Baseline F-score = 0.44, F-score = 0.60
Sen et al., 2018	Autoencoder	ASD and ADHD prognosis	Baseline ACC = 0.500–0.516, ACC = 0.643–0.673
Aghdam et al., 2018	DBN	Forecasting ASD	ACC = 0.656
Prasetio et al., 2018	CNN	Stress recognition	Baseline ACC = 0.890, ACC = 0.959
Tran and Kavuluru, 2017	Attention-based RNN, CNN	Prediction of 11 mental health issues (depression, anxiety, etc.)	Baseline F-score = 0.598, F-score = 0.631
Lin et al., 2017	CNN	Identification of stress	ACC = 0.916
Geng and Xu, 2017	CNN and Autoencoder	Depression prediction	Baseline ACC = 0.71, ACC = 0.95
Jaiswal et al., 2017	CNN	ASD and ADHD prediction	ACC = 0.96 (condition vs. HC), ACC = 0.93 (ADHD + ASD vs. ASD only)
Sadeque et al., 2017	GRU	Early depression prediction	Baseline F-score = 0.40, F-score = 0.64
Pinaya et al., 2016	DBN	Prediction of schizophrenia	Baseline ACC = 0.681, ACC = 0.736
Ulloa et al., 2015	DFNN	Schizophrenia prediction	Baseline ACC = 0.70, ACC = 0.75
Lin et al., 2014	DFNN and CNN	Stress detection	ACC = 0.756–0.844

Table 2 provides an in-depth overview of several studies conducted in the field of mental health evaluation between 2014 and 2019. Based on the author(s), year of publication, methods used, study cohort, purpose, and performance measures, each study is categorized. CNN, RNN, autoencoders, LSTM, gated recurrent units (GRU), and deep belief networks (DBN) are just a few of the methods used in these investigations. The group of people who are studied are very diverse; they include healthy controls as well as people with a range of mental health diagnoses, including bipolar disorder, schizophrenia, depression, ADHD, ASD, and stress. This research primarily aims to diagnose and predict mental health diseases, identify risk factors for suicide, detect stress, and identify abnormal brain anatomical patterns related to neuropsychiatric disorders. Performance measures like baseline comparisons, F-score, and accuracy (ACC) are used to assess how well the suggested approaches work. All things considered, this analysis offers insightful information about the varied methods and strategies applied in mental health research for the understanding, diagnosis, and prognosis of different mental health conditions. The goal of the study is to provide precise and effective tools for early detection, intervention, and individualized treatment planning in mental healthcare by utilizing cutting-edge ML and DL algorithms.

CHALLENGES AND FUTURE DIRECTIONS

This review highlights the effectiveness of image processing and deep learning (DL) techniques in Facial Expression Analysis (FEA) for mental health assessment, while also identifying key challenges and future directions. Cultural diversity remains a major concern, as variations in facial expressions across populations require the development of culturally adaptive models. Ethical considerations, particularly related to consent, privacy, and data security, must be prioritized to ensure responsible use of sensitive facial data.

Advancements in DL and image processing techniques offer opportunities to improve accuracy and reliability, encouraging the exploration of more robust and innovative models. Interdisciplinary collaboration among psychology, healthcare, and computer science is essential to create comprehensive and clinically relevant solutions. Additionally, ensuring validation and generalization across diverse populations and clinical settings is crucial for the broader applicability of FEA systems.

CONCLUSION

This study provides a concise review of image processing techniques used in FEA for mental health evaluation, emphasizing the importance of non-verbal cues, particularly facial expressions, in understanding psychological conditions. Techniques such as feature extraction, classification algorithms, and machine learning approaches demonstrate strong potential for detecting and monitoring disorders like anxiety, depression, and schizophrenia.

Despite challenges such as cultural variability and ethical concerns, FEA remains a promising tool for enhancing mental health assessment. Continued research, technological advancements, and interdisciplinary efforts will further strengthen its clinical relevance, ultimately improving diagnostic accuracy and patient outcomes.

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