

Enhancing Accuracy of Automated Depression Diagnosis Through Facial Expression Analysis and False Expression Mitigation

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Abstract – Depression is a pervasive mental health disorder affecting millions worldwide. Yet, accurate and precise depression diagnosis remains challenging due to its reliance on subjective reporting and interpretation of prospective patients. Facial expressions, as indicators of emotions, can be utilized as an objective method for enhancing diagnostic accuracy. This study presents a platform that integrates real-time facial expression analysis with a depression diagnostic tool, aiming to distinguish genuine from false, controlled emotional expressions. The platform uses a *face-api* for javascript to capture and analyze facial expressions in real-time while also administering DSM-5 depression analysis questions. In an exploratory study, participants were exposed to randomized video stimuli designed to obtain both controlled and authentic emotional responses. Such preliminary findings demonstrate the potential of advanced technology to detect emotional authenticity and bridge the gap between subjective self-reports and objective depression diagnostics. This study highlights a scalable, non-invasive approach to improve depression diagnosis accuracy and lays the groundwork for further development in clinical healthcare applications.

Keywords: Depression Diagnosis, Facial Expression Analysis, Emotional Authenticity Detection, False Expression Mitigation,

1. Introduction

Depression is a critical global health concern and is projected to become the leading cause of disease burden within the next 15 years [24]. It affects approximately 4–8% of children and 15–20% of adults at some point in their lives. In the United States, 9.2% of individuals aged 12 and older reported experiencing a major depressive episode in the past year, with the prevalence being notably higher among young adults (18–25 years) at 17.2% and adolescents (12–17 years) at 16.9% [12]. Alarmingly, the global prevalence of depression continues to rise, with an estimated 1% annual increase in cases. If these trends persist, millions more individuals are expected to be affected by 2030 [17]. Simultaneously, beyond its substantial impact on individuals, depression contributes to a global economic burden exceeding \$1 trillion annually due to lost productivity, healthcare costs, and social services [34].

Depression manifests in a wide spectrum of forms, including major depressive disorder (MDD), persistent

depressive disorder (PDD), bipolar depression, seasonal affective disorder (SAD), postpartum depression, psychotic depression, situational depression, and atypical depression [4]. Each subtype is characterized by unique features and diagnostic criteria, although they all share core symptoms such as low mood and diminished interest in external activities. The underlying causes, however, can vary significantly. For instance, MDD is frequently associated with traumatic experiences, such as childhood sexual, physical, or emotional abuse, which are known to significantly heightened vulnerability to depressive disorders [27].

The impact and consequences of depression extends beyond emotional distress, affecting cognitive [22], physical [35], and social functioning [18]. Cognitively, depression often impairs memory, concentration, and decision-making abilities, severely affecting daily activities and productivity [3,16,22]. Physically, individuals with depression commonly exhibit altered sleep patterns, changes in appetite, chronic fatigue, and even unexplained physical pain [35]. Socially, depression disrupts relationships,

reduces occupational performance, and diminishes overall quality of life [18,21]. These multifaceted impacts underscore the profound and pervasive nature of depression, further reinforcing the urgency for accurate diagnostic methods and effective interventions.

Conventional methods for depression diagnosis include patient interviews [8], self-report questionnaires, and clinical observations. Various methods exist for diagnosing the type and severity of depression, aiming to identify the type and severity of depression through various strategies. These methods are typically categorized into Psychological evaluation [30], Self-Reported questionnaires [19], Medical Testing and Exclusion Methods. Each method provides unique insights into depressive symptoms, though they often complement one another to improve diagnostic accuracy.

Psychological evaluation involves direct interaction between a mental health specialist, such as a psychiatrist, and the patient. These evaluations include patient interviews and clinical observations to assess mood, behavior, and overall mental state. Common techniques include the *Diagnostic and Statistical Manual of Mental Disorders* (DSM-5), a globally utilized framework that was initially developed in 1952 and most recently updated in 2013 [20]. The DSM-5 includes three main sections and provides guidelines for various disorders, offering a comprehensive set of criteria and standardized questions to aid in accurate diagnoses [20,32]. During evaluation, specialists may also observe non-verbal cues, emotional affect, and interpersonal behavior during these evaluations.

Self-Reported questionnaires involve patients completing standardized questionnaires designed to measure the severity and nature of depressive symptoms. Examples include the Patient Health Questionnaire-9 (PHQ-9), widely utilized in primary care for early detection of depression [32]. The PHQ-9 consists of nine questions that align with DSM-5 criteria and provides a scoring system to evaluate the presence and intensity of depressive symptoms. Another example is the Beck Depression Inventory (BDI), which examines cognitive, emotional, and physical symptoms of depression [11]. Such questionnaires and methods are efficient and cost-effective, allowing them ideal for usages in primary care or remote settings. Despite their utility, however, it is inevitable that these methods strongly rely on patients' honesty and self-awareness, which may lead to possible inaccurate results.

Medical testing and exclusion methods include physical exams and laboratory tests such as blood tests. Phosphate level blood tests, for instance, can lead to 82% of correct diagnosis of depression [36]. Other methods include substance use screenings that can help identify alcohol or drug misuse that could contribute to depressive symptoms [32]. While these methods do not diagnose depression directly, they aid in ruling out other medical conditions or external factors that may mimic or influence depressive symptoms.

Psychological evaluations offer significant strengths and benefits, particularly in providing personalized and nuanced insights into a patient's mental health status. Their strengths lie in the ability of clinicians to observe and interpret a wide range of factors, including verbal descriptions, non-verbal cues, and interpersonal behaviors. However, these evaluations inherently rely on subjective patient inputs, which can introduce variability and potential inaccuracies in diagnostic outcomes. Patients differ widely in personality traits, emotional articulation, and external circumstances, which can influence the diagnostic process.

For instance, introverted individuals may struggle to accurately convey their emotional states and symptoms during clinical assessments, leading to underreporting or misinterpretation by clinicians [12,31]. Children, in particular, often feel overwhelmed or intimidated in unfamiliar clinical environments, which can result in them closing off emotionally. Additionally, barriers such as limited medical literacy, language differences, or low educational attainment can significantly affect how patients describe their conditions. Trust issues may also arise, with patients withholding critical information due to a lack of confidence in their healthcare provider. Conversely, some patients might fabricate symptoms to obtain stronger medications, further complicating the diagnostic process. These factors, which lie beyond the control of physicians, underscore the inherent limitations of conventional psychological evaluations.

As mentioned above, standardized screening tools such as the Patient Health Questionnaire-9 (PHQ-9) have been integrated into primary care settings to improve early detection. However, despite their utility, current diagnostic approaches remain suboptimal, ranging from approximately 47%–63% accuracy level, indicating significant room for improvement [3]. General practitioners (GPs), who serve as one of the first points of contact for 76% of individuals seeking help for depression, often face additional

challenges. Studies reveal that GPs accurately identify only 51% of depressed patients compared to validated PHQ-9 measures [29]. These unavoidable limitations highlight the need for diagnostic enhancements that are both precise and adaptable.

Facial expressions, triggered by intricate neural mechanisms linking emotional states to muscle movements, offer a possible avenue for improving depression diagnosis [38]. Microexpressions - brief, involuntary facial movements - in particular, are highly revealing, as they often occur when individuals attempt to conceal their genuine emotions [2,39]. These subtle cues, often undetectable with the naked eye, can be leveraged to differentiate between authentic and controlled emotional states.

To address the fact that people can control their facial expressions to conceal their authentic emotional state, several studies were conducted around this component. For instance, previous research has shown that individuals with depression demonstrate diminished ability to voluntarily mimic or imitate their facial expressions [10]. However, these studies typically relied on human raters while also lacking comparisons between genuine and controlled facial expressions.

This study introduces a novel web-based platform concept that integrates facial expression analysis with DSM-5 depression diagnostic surveys and NLP to showcase the possible enhancement of depression diagnosis accuracy. Leveraging the *face-api.js* for JavaScript, the platform captures and analyzes facial expressions in real-time, aligning these observations with responses to patients' responses to DSM-5 depression analysis questions. Through exploring the future possibility of utilizing advanced technology to identify the authenticity of patients' responses, this exploratory study seeks to introduce a more objective framework and new methods of collecting data that can assist clinical professionals in their process of diagnosing patients.

2. Materials and Methods

2.1 Platform Development

The development of the platform for this study focused on leveraging advancements in *face-api.js* and real-time facial expression analysis technologies to create an innovative

diagnostic assistant tool for depression. Designed to operate with a standard webcam, the system captures, analyzes, and interprets facial expressions, providing an additional layer of insight into participants' emotional states during diagnostic evaluations.

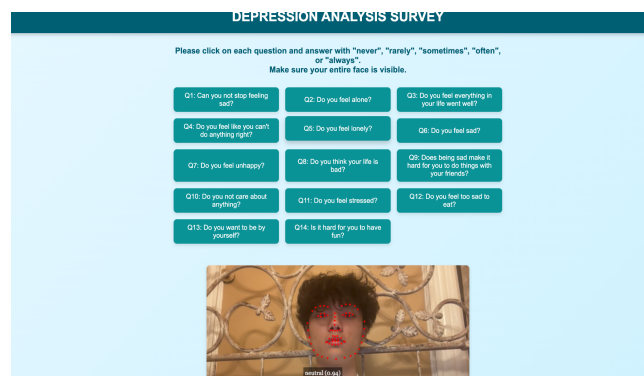


Figure 1. The original development of the platform with facial expressions analysis

The platform integrates 14 questions derived from the DSM-5 criteria for depression. These questions are presented to participants, who respond verbally using predefined scales ranging from "never" to "always." The system processes these verbal responses using speech-to-text technology and automatically calculates a depression score based on the standardized scoring mechanism outlined in the DSM-5.

The *face-api.js* library was implemented to track facial landmarks and analyze expressions dynamically. By monitoring subtle changes in facial features during participant responses, the system identifies microexpressions and other emotional indicators that may correlate with depression severity. This functionality enables real-time observation of participants' emotional states, complementing the insights gained from their verbal responses.

For the exploratory study, the platform was modified to accommodate a different workflow. Instead of analyzing facial data in real time, the system was adapted to process pre-recorded videos. Participants' facial expressions were recorded while responding to the DSM-5 questions or engaging with emotional stimuli. These pre-recorded videos were then uploaded to the platform, where the model analyzed the facial landmarks and expressions offline. This adjustment allowed for controlled testing and ensured a consistent evaluation environment, facilitating the exploration of the platform's analytical capabilities under

varying conditions.

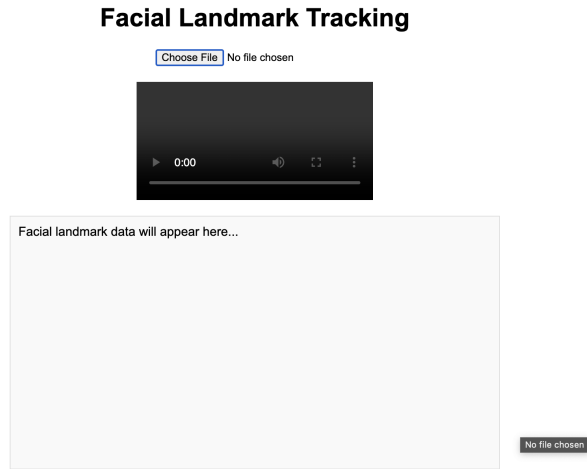


Figure 2. Modified version of the platform for the experiment

2.2 Authentic Expressions

Participants were instructed to watch five 15-second, PG-13-rated YouTube videos carefully selected to obtain six distinct emotions—happiness, sadness, anger, disgust, surprise, and neutral—corresponding to the emotional categories recognized by the *face-api.js* library. Before the videos began, a black screen was displayed for five seconds to record participants' baseline, neutral facial expressions, establishing a reference point for subsequent analyses.

To minimize order effects and participant bias, the sequence of videos was fully randomized for each participant. Following the viewing of each video, participants completed a brief survey to self-report the intensity of the emotion they experienced. This was rated on a 5-point scale, ranging from 1 ("not intense at all") to 5 ("extremely intense"). This survey data can be used to compare self-reported emotional intensity with the system's facial expression analysis, providing additional context for evaluating the platform's accuracy.

2.3 Controlled Expressions

In the controlled expression condition, participants were tasked with purposefully controlling their facial expressions to mimic the same types of emotions—happiness, sadness, anger, disgust, surprise, and neutral—that were obtained during the authentic expression phase. Participants were given explicit instructions to deliberately control these

emotional expressions, simulating how an individual might attempt to project specific emotions.

To ensure consistency and eliminate potential biases, the sequence of emotions was again randomized for each participant. They were then asked to perform the controlled expression for 5 seconds while being recorded.

The controlled expression data can be analyzed alongside the authentic expression data to compare variations in facial landmarks and microexpressions. This comparison provides insights into the platform's ability to differentiate between genuine and controlled emotional expressions and states.

2.4 Further Approaches

2.4.1 Normalization

The output of the data from the platform includes data of facial landmark coordinates. Since facial landmark coordinates vary across videos due to differences in face size, shape, and positioning within the video frame, normalization is necessary to ensure the comparability of data across participants and videos. Normalization aligns the facial landmarks to a consistent scale and reference point, possibly diminishing variabilities in the facial landmark data.

Initially, the facial landmark data should be centered by shifting the origin of the coordinate system to the center of the face. This can be defined as the midpoint between the inner corners of the eyes.

For each frame where x' and y' are the normalized coordinates and x_{center} , y_{center} represent the center point of the face,

$$x' = x - x_{\text{center}}, y' = y - y_{\text{center}} \quad (1)$$

Then, to account for differences in face size, all landmarks must be scaled relative to a reference distance, such as the distance between the eyes.

For each coordinate,

$$x'' = x'/d_{\text{reference}}, y'' = y'/d_{\text{reference}} \quad (2)$$

where $d_{\text{reference}}$ is the distance between the features, such as inter-pupillary distance.

Lastly, faces should align to ensure consistency in orientation. This is achieved by rotating the coordinates so that the line connecting the eyes is horizontal. The rotation

angle is calculated using the slope of the eye line.

$$\theta = \arctan(y_{\text{rightEye}} - y_{\text{leftEye}} / x_{\text{rightEye}} - x_{\text{leftEye}}) \quad (3)$$

Then, all coordinates are rotated using a standard rotation matrix.

$$x''' = x''\cos\theta - y''\sin\theta, y''' = x''\sin\theta + y''\cos\theta \quad (4)$$

The resulting normalized coordinates allow direct comparisons of collected data across participants and frames.

2.4.2 Calculation

In the experiment, a baseline neutral face was captured for each participant. Deviating each landmark from the average of the normalized coordinates of their facial landmarks during the capture of the neutral face is required.

For each landmark i and where N is the total number of frames for each video,

$$x_{\text{frame}}^i = \frac{1}{N} \sum_{k=1}^N x_k^i, \quad y_{\text{frame}}^i = \frac{1}{N} \sum_{k=1}^N y_k^i \quad (5)$$

For each frame, the deviation of each landmark from the neutral state is calculated.

$$\Delta x^i = x_{\text{frame}}^i - x_{\text{neutral}}^i, \quad \Delta y^i = y_{\text{frame}}^i - y_{\text{neutral}}^i \quad (6)$$

Using the delta values, the system can distinguish between authentic and controlled emotional expressions by analyzing patterns and intensities of facial landmark movements.

3. Conclusion

This study proposes a novel approach to improve the accuracy and objectivity of depression diagnosis by integrating advanced technology such as facial expression analysis with DSM-5 depression diagnostic surveys. Using the *face-api.js* framework, the platform captures and analyzes facial expressions with patients' responses to standardized diagnostic questions. By leveraging pre-recorded video data for offline analysis in this exploratory study, the platform demonstrates the potential for integrating advanced technologies into the diagnostic process. The proposed approach seeks to address existing

limitations in traditional methods by providing a more structured and objective framework for collecting and analyzing emotional and behavioral data. This study aims to contribute to the ongoing efforts in enhancing depression diagnosis accuracy and adaptability for future innovations in clinical and non-clinical mental health settings.

4. Discussion

4.1 Possible Results

The possible results of this research underscore the value of objective, data-driven tools in addressing challenges in depression diagnostics. The ability to differentiate between authentic and controlled emotional expressions has significant implications for clinical practice. Its ability to suggest that such systems could identify patients' genuine emotional state can be an assisting tool for professional clinicians.

4.2 Limitations

The study was conducted on a small sample size, limiting the generalizability of the findings. A larger, more diverse participant pool is necessary to validate the platform's effectiveness across different demographics, facial structures, and cultural contexts. The experimental design also focused on controlled laboratory conditions, which may not fully replicate real-world scenarios where lighting, background noise, and participant behaviors can vary. Finally, the system's accuracy and robustness need further optimization, particularly in edge cases such as individuals with extensive acting experience or atypical facial movements due to medical conditions.

4.3 Future Directions

Future work can address these limitations by expanding the participant base to include a more diverse range of ages, genders, and emotional expression capabilities. Improvements to the algorithm, including the use of transfer learning and fine-tuning on context-specific datasets, may help mitigate biases and improve performance. Moreover, field studies in real-world clinical settings can be conducted to evaluate the system's applicability and reliability outside the laboratory environment. Ultimately, integrating this platform into broader diagnostic frameworks and exploring its use alongside traditional methods could possibly conduct the way for a more optimal and personalized

technology-enhanced mental health care.

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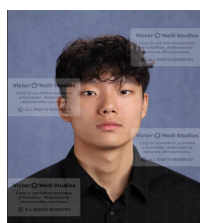
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