Journal of
Mobile Computing, Communications & Mobile Networks

ISSN: 2349-901X
Volume 12, Issue 3, 2025
September–December
DOI (Journal): 10.37591/JoMCCMN

https://journals.stmjournals.com/jomccmn

Research JoMCCMN

AI-Driven Micro-Expression Recognition for Early Mental Health Disorder

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Abstract

Mental health conditions like anxiety and depression are often undiagnosed because the usual diagnostic methods based on basic regular instruments like questionnaires and clinical interviews have some limitations in them. They are not objective often and may not catch the initial signs of psychological distress. Micro-expressions have become valid measures of repressed or unconscious emotions and can provide greater insight into someone's mental condition. Also, identification and interpretation of these micro-level cues in real-time is very challenging and usually needs the assistance of AI-powered technologies. This research examines how artificial intelligence, and specifically deep learning structures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, can improve the micro-expression analysis to aid early mental health disorder diagnosis. The findings of AI-generated analysis are compared with conventional approaches using accuracy, speed, and scalability as measures. This model will also discuss the value of including multimodal data, like voice tone and physiological signals. This will enhance diagnostic accuracy further. Even though early results are encouraging but ethical considerations about data privacy, fairness, and openness need to be addressed. This study seeks to contribute to AI systems that enable timely, accurate, and ethically robust mental health assessment.

Keywords: Artificial intelligence (AI), micro-expression recognition, mental health diagnosis, deep learning

INTRODUCTION

Mental Health Disorders and Diagnostic Limitations

The behavioral and mental health disorders that include depression, anxiety, and bipolar disorder often remain undetected in their early stages due to their subjective nature and also because they tend to hide their emotions [1]. These methods typically depend on patient interviews, self-reported questionnaires and clinician evaluations, which are likely to be patient dishonesty, misunderstanding, or clinician bias [2]. As time goes by, cases of mental health are rising linearly up and the need for accurate diagnosis has become serious. According to the World Health Organization, depression is projected to become the leading cause of disease problems globally by 2030 [2].

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Received Date: August 13, 2025
Accepted Date: September 20, 2025
Published Date: September 29, 2025

Citation: Charu Srivastav, Aadya Mishra, Rinku Raheja, Prabhash Chandra Pathak. AI-Driven Micro-Expression Recognition for Early Mental Health Disorder. Journal of Mobile Computing, Communications & Mobile Networks. 2025; 12(3): 40–49p.

Role of Micro-Expressions in Mental Health Detection

Micro expressions are unconscious facial displays of emotion that occur when someone is trying to hide their true feelings. Ekman [3] identified these delicate expressions as indicators of true feelings even when an individual attempts to mask

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them [4]. Unlike regular facial expressions, micro-expressions are difficult to control, making them a dependable source for detecting hidden emotions associated with mental health conditions [5]. However, these passing expressions are challenging to observe and cannot be analyzed without technological assistance [6].

The Emergence of AI in Micro-Expression Analysis

Artificial Intelligence (AI) technologies offer some feasible solutions for detecting and analyzing the micro-expressions [5]. Advanced AI models particularly in Machine Learning (ML) and Deep Learning, can process large datasets and recognize complex patterns. Techniques like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have proved high accuracy in facial emotion recognition, including micro-expressions [6]. These AI-driven systems would change the overall approach to mental health checkups. Additionally, AI can monitor facial patterns over time, allowing for early intervention when detecting emotional distress [7].

RESEARCH QUESTIONS AND OBJECTIVES

This research aims to explore how AI-based micro-expression recognition can improve early identification of mental health issues. It addresses the following key questions:

- How does AI cognition in micro-expression evaluation enhance early detection of mental health disorders?
- What are the current AI techniques used in emotion detection, and how suitable are they for clinical implementation?
- What ethical considerations and barriers exist in utilizing AI for diagnosing mental illnesses?

The primary objective is to review existing research and technological advancements in this domain and the scope for future developments.

SIGNIFICANCE OF THE STUDY

The significance of this research lies in helping a more accurate, non-invasive, and scalable approach to mental health issues. To reduce the long-term impact of mental disorders, early diagnosis is important. Conservative diagnostic practices often bank on individual interpretations and patient self-disclosure, which may not accurately reflect emotional distress [1]. Using AI-powered micro-expression analysis, mental health assessments would be more objective and data-driven [5].

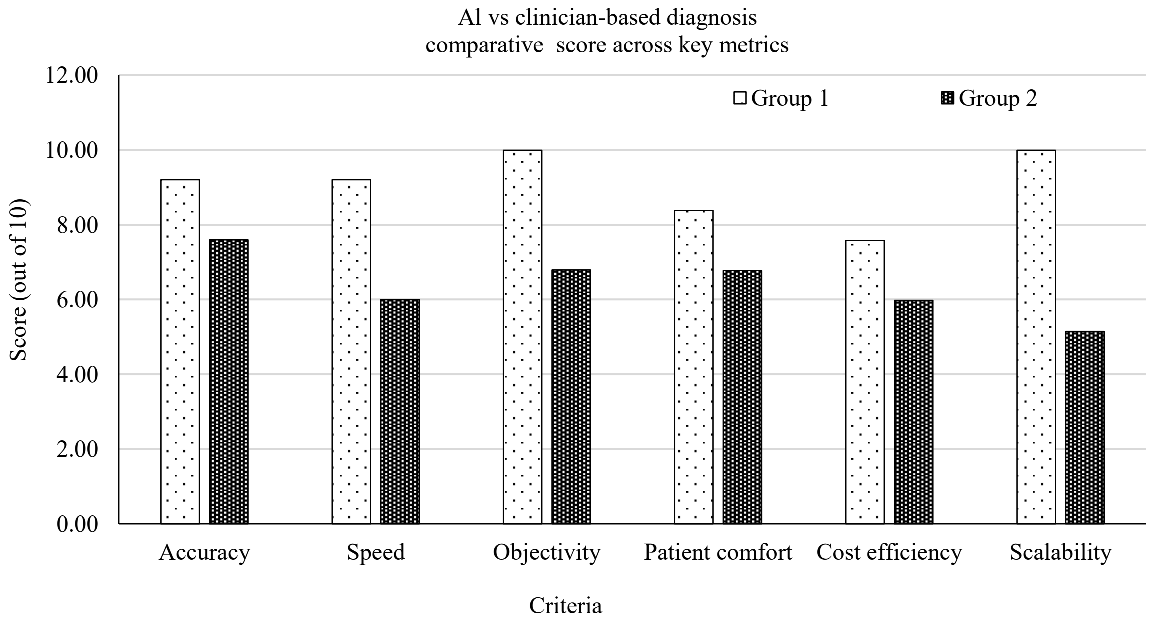

Figure 1. Comparison of AI model and traditional method.

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Figure 1 illustrates the comparison between AI-based detection and traditional clinician-based diagnosis, it highlights the potential of AI in this changing early mental health diagnosis [6]. This graph was made in Python using Matplotlib. AI-driven methods show superior performance in accuracy, speed and objectivity due to their ability to analyze large datasets and find the micro emotional cues [7].

RELATED WORK

Here are five recent models or methods developed for AI-driven micro-recognition aimed at early mental health disorder detection:

Deep Learning for EEG Signal Analysis

This model gained a high accuracy of about 93 to 95% in classifying EEG signals, presenting its ability to process neuroimaging data effectively [8]. Firstly, EEG signals are filtered to remove noise, and then FFT (Fast Fourier Transform) is used to transform complex signals into the frequency domain to extract meaningful patterns.

Equation:

$$X(f) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi f\, n/N} \tag{1}$$

where:

- X(f) is the transformed EEG signal,
- x(n) is the original time-domain signal,
- N is the number of samples, and
- $e^{-j2\pi f\, n/N}$ is a complex exponential function that helps decompose the signal into its frequency components.

It focuses on objective data and minimizing partiality in mental health assessments. However, it is limited to EEG data only and is available for use, requiring specialized equipment and expertise. It may ignore multimodal aspects such as verbal cues that are very critical for full mental health diagnostics. It comes with some limitations that affect diagnostic accuracy like it does not work for socio-cultural factors or biases in mental health [8, 9].

XAI For Mental Health Detection

This model includes understandable features like syntactic complexity and sentiment analysis, which enhances transparency and trust in AI models while abusing domain-specific transformers, personalized for mental health applications to improve accuracy [10]. It uses the TF-IDF technique to highlight important words associated with depression or anxiety (e.g., “hopeless”, “alone”). TF-IDF scores are used to justify why certain words were flagged as indicators of mental health issues.

Equation is as follows:

$$TF - IDF = TF \times log\left(\frac{N}{DF}\right) \tag{2}$$

where:

- TF (Term Frequency) represents how often a word appears in a document.
- N is the total number of documents in the dataset.
- DF (Document Frequency) is the number of documents containing the term.

However, it is dependent on verbal features and may exclude non-verbal cues such as micro-expressions or physiological signals, and explainability methods like LIME might generalize complex mental health phenomena, leading to potential misinterpretations. In addition, the model struggles with cultural sensitivity and partialities in training data, which can result in inaccurate diagnoses for minority populations and it requires constant updates to adjust to evolving mental health research and diagnostic criteria [11, 12].

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Multimodal AI Models for Depression Detection

This model combines facial expressions, voice features, and physiological signals like pupil dilation, which offers a full method for depression detection while representing improved exactness by leveraging diverse data sources [13]. However, multimodal systems are intensive and require real-time data collection across different modalities, artificiality challenges in real-world settings, and within-group variations often exceed between-group differences, which helps in reducing reliability. When models classify the state of mental health, Softmax Activation is used to assign probabilities to different classes [14]. It ensures that depression severity levels are interpreted as probability distributions.

Equation:

$$p(y_i) = \frac{e^{z_i}}{\Sigma_j e^{z_j}} \quad (3)$$

where:

- $P(y_i)$is the probability of class i (e.g., depression level).
- $z_i$is the model's raw prediction score for class i.
- The denominator ensures all class probabilities sum to 1.

Moreover, the model struggles with ecological soundness as lab-based data may not generalize well to real-life scenarios and may fail to hold understated cultural expressions of distress or emotional states with accuracy [10, 9].

Generative Network for ADHD Diagnosis

This approach uses autoencoder-based generative networks to process complex neuroimaging data with ease and achieves a moderate classification accuracy of 67%, showing ability in ADHD detection using multimodal features [15]. And use Reconstruction loss to compare the input and output of the model. When ADHD patients show deviations in neuroimaging data, the error is high which helps to detect ADHD based on brain function abnormalities.

Equation used here is as follows:

$$L = \left\|X - \hat{X}\right\|^2 \quad (4)$$

where:

- X is the original input data (e.g., EEG or fMRI scan).
- $\hat{X}$ is the reconstructed version produced by the model.
- L represents the squared reconstruction error, which quantifies how well the model is able to reproduce the original input.

The squared error ensures larger mistakes are penalized more.

However, it has relatively low accuracy compared to other methods, suggesting a need for further refinement in feature extraction processes, and its reliance on neuroimaging limits' accessibility and scalability in conceptual settings. Additionally, it fails to mix behavioral or emotional markers, which is a crucial part of ADHD diagnosis beyond neuroimaging data, and does not address ethical concerns such as "stealth science" or transparency in algorithm development [16].

AI-Driven Micro-Expression Recognition in Video Consultations

This method holds up computer vision techniques to detect soft facial movements during video consultations which enables remote monitoring of mental health conditions and offers scalability through mobile apps and telehealth platforms [17]. Euclidean Distance is used to measure micro-expression intensity. Micro-expressions are calculated over milliseconds; if movement exceeds the threshold, it may indicate emotions linked to mental health conditions.

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Equation for the above method is:

$$D = \sqrt{(a_2 - a_1)^2 + (b_2 - b_1)^2} \quad (5)$$

where:

- (a_1, b_1) and (a_2, b_2) are the coordinates of two facial landmarks (e.g., eyebrow raise, lip curl).
- D represents how much a facial feature has moved between two frames [18].

However micro-expression analysis is sensitive to variations in lighting, camera quality, and user posture, reducing consistency in uncontrolled environments, and may misread cultural expressions of tension due to a lack of cultural sensitivity in algorithms [17, 9]. In addition to this, it does not address challenges like small sample sizes or the poor ecological validity of training datasets used for micro-expression analysis models, and concerns related to privacy during video analysis remain unresolved, limiting user trust and adoption.

Limitations and Challenges of these Models

Analyzing all the above models, we conclude some problems which are not solved by these models. These are:

- Cultural sensitivity;
- Ecologic validity;
- Integration with clinical practices; and
- Transparency issues.

PROPOSED METHODOLOGY

If we look to the limitations and challenges of the above AI models for recognition of micro expressions in health detection, a new framework can be proposed: Culturally Adaptive Multimodal AI for Mental Health Detection (CAM-MHD).

Aim

To integrate multimodal data sources, enhance cultural sensitivity, improve ecological validity, and ensure transparency while maintaining high accuracy and real-time performance.

The Architecture of the Proposed Model

Majorly, it combines three components:

1. *Multimodal Data Integration:* This model will incorporate facial micro-expressions, voice features, physiological signals, and even textual data from social media or self-reports. This will integrate data from a hybrid deep learning architecture which will enhance accuracy. In this, a hybrid deep learning architecture will be used: for image-based micro-expression, CNN will be used; for sequential voice/text data RNNs will be used; and a feature fusion layer will be used to integrate these models. To fuse these features together, we will employ an attention-based convolutional fusion layer, ensuring each modality contributes dynamically based on its relevance. The fusion process is defined in Eq. (6):

   F_fused = Conv (Attention (Concat ([F_face, F_voice, F_EEG, F_text]))) (6)

   where:

   - F_face, F_voice, F_EEG, F_text represent feature maps from micro-expressions, vocal tone analysis, brainwave activity, and linguistic sentiment analysis, respectively.
   - Concat denotes the concatenation of these feature maps.
   - Attention is an attention mechanism that learns to weight each feature map dynamically.
   - Conv represents a convolutional layer that fuses the weighted feature maps into one representation [19, 20].
2. *Cultural Adaptation module:* This layer will be culturally advanced; it will be embedded into the model to account for sociocultural differences in linguistic patterns and emotional expressions as

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shown in Figure 2. Transfer learning techniques will be used here with region-specific datasets to change the predictions for the large population [21].

3. *Explainability and Ethical Design:* The model will incorporate explainable AI techniques like LIME or SHAP to provide transparent insights into its decision-making process, ensuring clinicians and patients can understand the justification behind predictions. To ensure that it is an ethical design, a fairness metric is monitored during training, and to mitigate potential biases related to protected attributes, adversarial debiasing techniques will be applied [22, 23].

Required Datasets and Preprocessing

Datasets

It will require a wide extent of differing datasets which can combine facial expression recordings like CASME and SAMM, voice recordings like DAIC-WOZ, physiological signals from wearable gadgets, and multilingual social media posts, for case, Twitter and Reddit. To train the model effectively within convolutional fusion layer, datasets should be an expanded range of emotional expressions and cultural contexts [24]. Publicly available datasets can be augmented with region-specific data through partnerships with mental health organizations [25]. Figure 3, depicts the ratio of facial expressions, voice recording, physiological signals and social media data, which we can use in the CAM-MHD. This is a hypothetical graph that has been generated in Python using matplotlib [26, 27].

Preprocessing

Data preprocessing will include normalized facial Expression videos across varying light conditions for precise alignment, converted audio signals into spectrograms, Physiological Signals using wavelet filtering and segments into fixed-length and for sentiment analysis text data. Data augmentation methods will address small sample sizes by generating synthetic examples using generative adversarial networks (GANs) as shown in Figure 4.

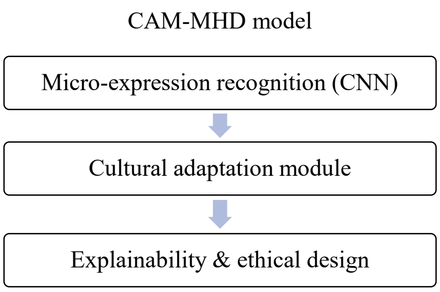

Figure 2. Model of CAM-MHD.

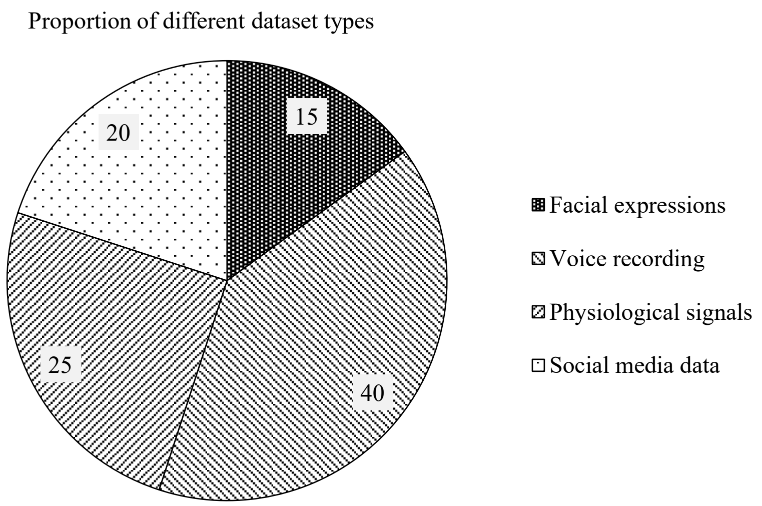

Figure 3. Proportion of different types.

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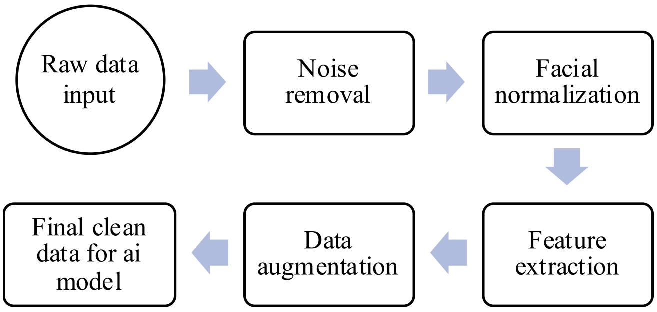

Figure 4. Data Preprocessing Pipeline.

Table 1. Methodology comparative analysis of proposed methodology with the other one.

Feature	Deep Learning (EEG)	XAI for Mental Health	Multimodal AI	Generative Network (ADHD)	AI-Driven Micro-Expression	Proposed CAM-MHD
Data Modalities	EEG signals	Linguistic features	Facial, voice, physiological	Neuroimaging	Facial micro-expressions	Facial, voice, physiological, text
Accuracy	93–95%	High in text-based analysis	Moderate to high	67% (ADHD detection)	Depends on video quality	High (through multimodal fusion)
Ecological Validity	Low (requires specialized EEG setups)	Moderate	Low to moderate	Low (clinical settings only)	Moderate (real-world video consultation)	High (real-time, wearable AI integration)
Cultural Sensitivity	No adaptation	Limited adaptation	Low (one-size-fits-all)	No adaptation	Lacks cultural sensitivity	Cultural Adaptation Module for region-specific learning
Computational Complexity	High	Moderate	High (requires multimodal fusion)	High	Moderate	Optimized with edge computing for real-time processing
Scalability & Accessibility	Low (EEG setup required)	Moderate (text-based models are scalable)	Low (hardware-intensive)	Low (requires MRI, fMRI)	Moderate (video-based)	High (deployable via telehealth and mobile applications)
Explainability	Black-box AI	High (XAI methods)	Low to moderate	Low (generative models are hard to interpret)	Low (black-box CV models)	High (SHAP/LIME for decision transparency)
Clinical Integration	Limited (not widely used in practice)	Moderate (some NLP-based tools exist)	Experimental stage	Early research phase	Limited to research settings	Designed for real-world healthcare deployment

Potential Improvements that this model should imply are:

- *Real-Time Processing:* This model will show real time processing using a complex method to combine information. It will be focusing on the most important details to save time.
- *Enhanced Accuracy:* The model will be better at understanding how different types of information are related to each other.
- *Scalability:* The model can be made powerful by adding more layers or by just expanding its focus.
- *Ethical Safeguards:* it ensures that it is not biased but fair.

Theoretical framework

This study of AI-driven micro-expression recognition for mental health detection relies on many theories, including affective computing, multimodal data fusion, and explainable AI [28]. The CAM_MHD model builds on existing literature by incorporating these principles while referring to the gaps in ecological validity, cultural sensitivity, and ethical AI design.

1. *Affective computing and emotion recognition:* Micro-expressions are rapid, involuntary facial expressions and existing AI models operate within the domain of affective computing but often fail for real-world variability. CAM-MHD would correct this problem [25].
2. *Multimodal AI in Mental Health Analysis:* Traditional models have demonstrated success in detecting depression but remain limited in their ability to generalize across populations. CAM-MHD enhances robustness with facial micro-expressions, physiological signals, and textual data for more assessment [29].
3. *Cultural and Ethical Considerations in AI:* Many AI models suffer from cultural bias due to non-diverse training data. CAM-MHD uses a Cultural Adaptation Module that changes predictions based on sociocultural variations in emotional expression, ensuring inclusivity. AI methods like SHAP and LIME increase transparency, making the model interpretable for both clinicians and patients.

This framework provides a foundation for comparing existing models with CAM-MHD in terms of accuracy, scalability, inclusivity, and clinical applicability as shown in Table 1.

CONCLUSION

The Culturally Adaptive Multimodal AI for Mental Health Detection (CAM-MHD) system increases accuracy, inclusivity, and real-world applicability in AI-driven mental health detection by using multimodal data sources such as facial micro-expressions with voice highlights, physiological signals, and content examination. Its social adaptation module progresses affectability to socio-cultural contrasts, reducing inclination and improving common results over assorted populations, whereas its clarifying methods advance transparency and belief among clients.

Future investigations should center on real-world approval through clinical trials, optimizing computational effectiveness for real-time handling on edge devices, reinforcing information protection with procedures like unified learning, progressing cross-cultural versatility through region-specific datasets, and joining CAM-MHD into healthcare frameworks for consistent appropriation in diagnostics and therapy. Tending to these challenges will empower CAM-MHD to revolutionize early mental well-being clutter discovery by giving a versatile, exact, and morally sound AI-powered arrangement for people, clinicians, and analysts around the world.

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