AI-driven emotion recognition systems for sustainable mental health care: an engineering perspective

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ABSTRACT

Emotion recognition systems are transforming human-computer interaction (HCI) applications by enabling AI-driven, adaptive, and responsive mental health interventions. This study explores AI-based emotion recognition technologies using facial expressions, voice analysis, text-based sentiment processing, and physiological signals to develop scalable, real-time mental health support systems. Utilizing datasets such as FER2013, JAFFE, and CK+, our research examines deep learning models, including EfficientNet-XGBoost, which achieved over 90% accuracy across key evaluation metrics. Unlike traditional mental health interventions, AI-driven systems provide cost-effective, accessible, and sustainable solutions through telemedicine, wearable biosensors, and virtual counselors. The study also highlights critical challenges such as algorithmic bias, ethical AI compliance, and the energy consumption of deep learning models. By integrating machine learning, cloud-based deployment, and edge computing, this research contributes to the development of sustainable, ethical, and user-centric AI solutions for mental health care. Future directions include AI model optimization for energy-efficient deployments and the creation of diverse, inclusive datasets to improve performance across global populations.

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1. INTRODUCTION

Mental health literacy involves the knowledge, beliefs, and attitudes concerning mental health disorders, influenced by individual, cultural, and social factors [1]. Although technology-based interventions provide scalable solutions, cost, accessibility, and stigma still hamper their reach [2]. Stigma, especially, discourages patients from receiving treatment, underlining the necessity for AI-enabled platforms and community education to raise awareness and early detection [3]. Personality factors such as extraversion and neuroticism, according to the big five theory, have a large bearing on mental health outcomes [4]. The COVID-19 pandemic revealed deficiencies in mental health services and accelerated the use of AI-powered chatbots such as Siri and Alexa to screen and assist [5]. Combining clinical approaches with positive psychology and digital technologies can enhance long-term psychological well-being by developing resilience and emotional resilience [6]. Emotion recognition is vital for social interaction through the interpretation of dynamic cues, such as movement direction and quality that add to emotional understanding and commitment [7]. Dynamic displays are particularly effective at capturing early attention during difficult conditions, facilitating emotional recognition and anticipation. With increasing importance in applications such as human-computer interaction (HCI), virtual reality, and medicine, emotion recognition is increasingly investigated using electroencephalogram (EEG) signals, although subject-independent analysis remains challenging [8]. Developments in AI and deep learning, specifically EEG-based brain-computer interface (BCI) methods, are facilitating machines to better classify emotions [9]. Facial expression recognition, aided by convolutional neural networks (CNNs) and temporal models such as recurrent neural networks (RNNs) and long short-term memory (LSTMs), enhances recognition further through the use of geometric and appearance features independent of large-scale pre-processing [10].

This research fills gaps in existing mental health care systems by investigating the potential of AI-powered emotion recognition from facial expressions, voice, and physiological signals to facilitate empathetic and timely intervention through HCI. It addresses central challenges such as algorithmic bias, data privacy, and cross-cultural diversity, providing engineering and ethical solutions to improve scalability, inclusivity, and trust. Emotion recognition is framed as a groundbreaking technology for tailored, responsible mental health treatment, with the subsequent sections looking into some of the most significant methods, including speech analysis, natural language processing (NLP)-based text emotion detection, facial expression recognition, and physiological signal monitoring using wearables. Table 1 overviews these methods, outlining their techniques, advantages, disadvantages, accuracy, and popular datasets.

Table 1. Summary of key approaches in emotion recognition

Category	Key features	Core technologies/ methods	Datasets used	Applications	Performance metrics	Challenges and limitations	References
Facial emotion recognition (FER)	Detects identity, age, and gender.	- CNNs - Transfer learning (EfficientNet-XGBoost)	- CK+ - KDEF - JAFFE - FER2013 - AffectNet	- Education (student monitoring) - Healthcare (pain monitoring) - Driver fatigue/emotion detection	- 69.3%: Masked Faces (AffectNet dataset) - 99.69%: KDEF dataset	- Lower performance in masked images - Dataset biases (e.g., fewer diverse samples) - High computational cost for real-time processing	[11]–[13]
Voice emotion recognition	Relies on audio features like pitch, energy, spectrograms	- Acoustic signal analysis (MFCC, LPCC coefficients) - Log-mel spectrograms	- RAVDESS - LDC database - UGA Databases	- Speech-based mental health monitoring - Multimodal emotion detection - Human-robot interaction	- 68%: Log-Mel spectrogram with 2D CNNs - 80.86%	- Audio feature selection impacts accuracy - Poor generalization across accents/languages	[14]–[18]
Textual emotion analysis (TEA)	- Explores emotional polarity in text using NLP. - Analyzes real-time data (e.g., COVID-19 tweets).	- Deep learning-aided semantic text analysis (DLSTA) - Emoji-oriented analysis - Cross-linguistic NLP approaches - Sentiment analysis tools	- COVID-19 Twitter data - UK parliamentary debates - Large social media datasets	- Sentiment monitoring on social media - Personalized AI systems (e.g., chatbots) - Political sentiment prediction	- 97.22% Detection rate: DLSTA - 98.02% accuracy	Limited by the availability of large-scale labeled datasets	[19], [20]

2. PROPOSED METHOD

HCI and affect recognition technologies are being applied more and more to augment empathetic, responsive reactions in fields such as mental health, education, and healthcare. While HCI-based mental health applications have grown, issues persist, ranging from inadequate design assessment, cross-cultural obstacles, absence of patient-focused ethics [21], usability problems [22], and poor comprehension of digital therapeutic alliances (DTA) [23]. Rising solutions, including deep learning-based emotion recognition frameworks [24] and human-centered machine learning (HCML) based on social media [25], hold potential but demand attention to privacy, ethics, and user participation.

2.1. Emotion recognition as an interface in human-computer interaction
Emotion perception is emerging as the focus for (HCI), allowing systems to recognize human emotions via facial expression, voice, and physiology, enhancing empathy and user experience in health, education, and services. Methods such as dynamic facial emotion recognition from action units and neural networks [26], adaptive user interfaces from RGB-D sensors [27], and multimodal recognition from EEG and facial expressions show high performance and promise. Deep learning, transfer learning [28], and principal component analysis (PCA)-based modeling [29] further improve recognition performance, whereas thermal video analysis with faster R-CNN and BCI extend HCI capabilities. Nevertheless, pose variation, lighting, and the absence of subject-independent EEG models still pose challenges, calling for greater socio-behavioral insight and experimental frameworks towards trustworthy HCI systems.

2.2. Human factors in human-computer interaction for mental health applications
Human factors of HCI for mental health apps are focused on user-oriented design principles with emotional sensitivity, easy-to-use interfaces, and privacy to ensure trust and participation. Albeit the increased prevalence of mental health apps, poor usability, restricted flexibility, and absence of empathic design stand in the way of broad adoption, as stressed in user feedback [30]. Research indicates that using human factors models enhances usability in health IT systems [31], but numerous technologies are still hard to use, regardless of advances such as big data and NLP. Cultural, social, and policy obstacles also impact adoption, particularly among vulnerable populations [32]. Although technologies such as mobile screening applications, chatbots, and internet interventions hold promise, long-term use is contingent upon having ethical controls, human contact, self-reflection, and social connectivity features.

3. RESEARCH METHODOLOGY
The study's research technique is shown in Figure 1, a swimlane flowchart is oriented. The “study design” step, which outlines a mixed-methods approach to emotion identification and HCI, comes first. The “inclusion and exclusion criteria,” which guarantee that only the most pertinent studies are included within the scope of the study, come after the “search strategy” phase, which details the methodical search for pertinent literature.

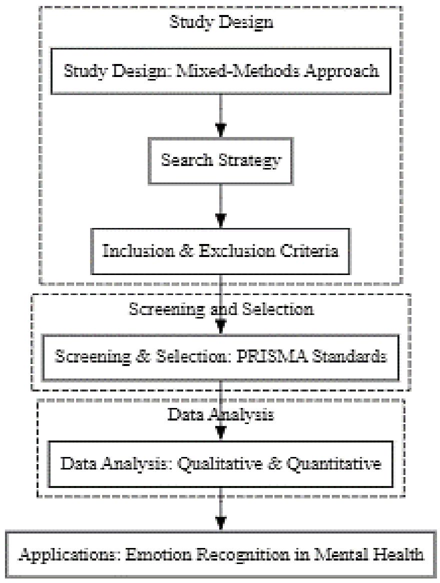

Figure 1. Research methodology overview

The “screening and selection” step emphasizes how PRISMA standards are followed while conducting a systematic review of papers. The “data analysis” section captures the overall qualitative and quantitative methodology carried out for extracting insights from performance and user experience regarding models. Lastly, the “applications” phase uncovers the practical application of emotion recognition technology in mental health and well-being. This flowchart is a structured, visualized summary of research methodology, ensuring clarity and comprehensiveness.

3.1. Study design

This study involved a mixed-methods review strategy to give an all-rounded appreciation of HCI and the recognition of emotions in psychology and well-being. Technological effectiveness, user engagement, challenges, and the social impact of emotion recognition applications are further explored through the integration of quantitative and qualitative data. A systematic search approach was used to find pertinent studies of emotion recognition in HCI for mental well-being, as outlined in Table 2, which provides a breakdown of the number of papers retrieved from various databases using targeted keywords. A review of peer-reviewed studies solely centered on emotion recognition embedded within HCI, including both quantitative measures (e.g., accuracy and effectiveness) and qualitative information (e.g., user experience) for an exhaustive interpretation, was included. Technologies directly applicable to mental health interventions, including chatbots, wearable technology, and virtual therapists, were prioritized because of their direct impact. Non-emotion-detection-focused studies and studies that were not relevant to HCI or mental health were excluded, as well as non-peer-reviewed or anecdotal sources, in order to keep the research rigorous. Applying a PRISMA-guided systematic screening process, titles and abstracts were initially screened for relevance, followed by full-text examination, finally leading to the selection of 55 high-quality studies for detailed evaluation.

Table 2. Search strategy summary

Keyword	Scopus	IEEE Xplore	PubMed	Google Scholar	ScienceDirect	Total papers found
Emotion recognition	85	60	25	130	45	345
HCI	90	110	10	180	65	455
Mental health technologies	70	25	95	150	80	420
Digital health tools	50	30	75	100	55	310
Telehealth and AI	45	55	85	120	50	355
Adaptive mental health apps	40	20	60	80	30	230
HCI for mental well-being	65	50	40	95	40	290

4. RESULTS AND DISCUSSION

The selected emotion recognition strategy utilizes cutting-edge methods such as CNNs, transfer learning, and multimodal analysis to provide high accuracy and scalability across real-world applications. The methods successfully solve issues such as masked faces, low-light environments, and subtle voice cues, while continuous, non-invasive emotional monitoring is facilitated through the integration of physiological signals and wearable technologies. By integrating deep learning with machine learning, this holistic paradigm provides strong, empathetic, and contextual solutions for real-time emotion detection in healthcare, education, and autonomous systems. Data extraction in this study was conducted with a standardized form to ensure that the important details were collected in an organized manner from chosen studies, such as author details, publication year, aims, methodology, results, and technologies used. Quantitative measures, for instance, the accuracy of emotion recognition, as well as qualitative factors like user interaction and ethical issues, were noted for an overall understanding. The quantitative analysis presented in Figure 2 compared four models of emotion recognition based on accuracy, precision, recall, and F1-score showing EfficientNet-XGBoost to be the best, followed by the ensemble classifier. Figure 3 also shows trends in dataset usage, where FER2013 has been the most utilized (30%), followed by JAFFE (25%), CK+ (20%), KDEF (15%), and AffectNet (10%), showing both the increase and trends in dataset choice over the years.

To gain a deeper insight into the popularity and performance of emotion recognition datasets, their usage patterns were examined, helping evaluate their appropriateness for algorithm training and testing. Figure 4 depicts the technology adoption curve of emotion recognition solutions from 2015 to 2021 with associated implementation challenges. Even as adoption has continued to grow, an interesting departure from the challenges trend is observed from around 2018, indicating that primary ethical and technical hurdles have been slowly overcome showing increased acceptance and incorporation of emotion recognition technology in real-world applications. A mixed-methods approach was employed to evaluate the effectiveness and challenges of AI-based emotion recognition in mental health applications. Quantitative analysis assessed model performance highlighting top performers like EfficientNet-XGBoost and ensemble classifiers based on accuracy, precision, recall, and F1-score while qualitative thematic analysis revealed critical barriers such as societal stigma, privacy concerns, and usability issues. The integration of findings emphasizes that although emotion recognition models show strong technological potential for real-time, personalized mental health support (e.g., via chatbots or virtual therapists), ethical, cultural, and computational challenges must be addressed to ensure effective and inclusive adoption in real-world settings.

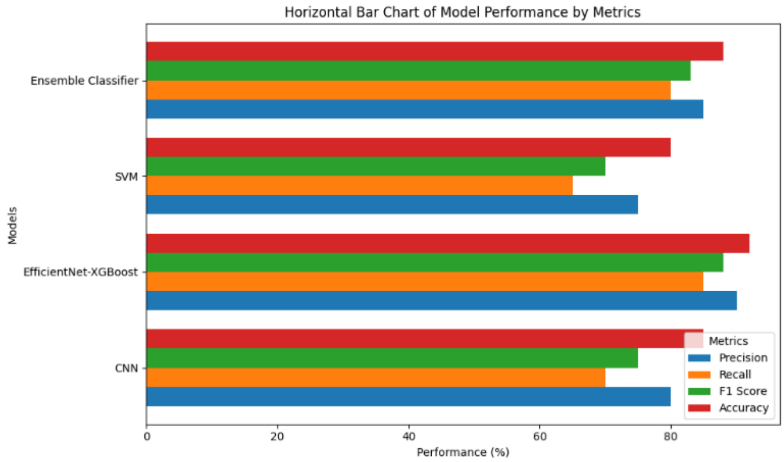

Figure 2. Model performance on different metrics

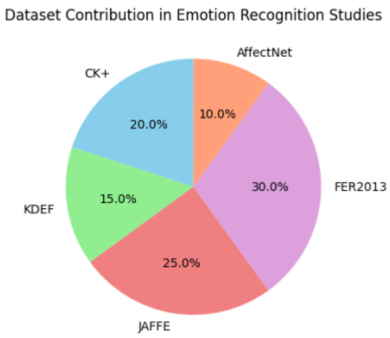

Figure 3. Dataset contribution in emotion recognition

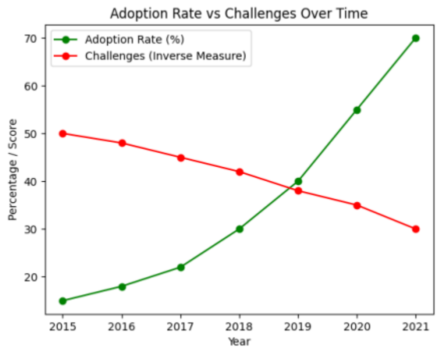

Figure 4. Adoption rate vs challenges over time

5. CONCLUSION

Emotion recognition technologies are transforming mental health treatment by providing individualized, AI-based interventions through virtual therapists, adaptive platforms, and telehealth systems. Through data sets including FER2013 (30%), JAFFE (25%), and CK+ (20%), improving model precision EfficientNet-XGBoost over 90% adoption rates have crossed 70% as of 2021, indicating advancement in transversing ethical and technical challenges. Even with this growth, challenges such as data privacy, algorithmic bias, and limited dataset diversity need to be resolved so that the creation of dependable, accessible, and scalable solutions is promoted. Future studies must target ethical AI models, multivariate datasets, energy-optimized models, and user-centered design to augment the scalability and accessibility of emotion recognition in mental health. This research acknowledges the revolutionizing potential of emotion recognition by AI for developing empathetic, accessible, and effective mental health care systems.

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AUTHOR CONTRIBUTIONS STATEMENT

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Akram Ahmad	✓	✓	✓	✓	✓	✓		✓	✓	✓				
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Kamal Upreti	✓		✓	✓		✓			✓		✓	✓	✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [SSA], upon reasonable request.

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