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Mooditor: An AI-Powered Mobile Assistant for Real-Time, Emotion-Aware Mental-Health Support

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ABSTRACT

Abstract: Mooditor is a pioneering mobile and web-based application designed to enhance mental health monitoring through artificial intelligence. By integrating real-time emotion detection via facial expression analysis and a Rasa-powered chatbot for therapeutic interactions, Mooditor provides a multi-modal approach to mental well-being. The system leverages computer vision and natural language processing (NLP) to assess psychological states, offering continuous monitoring and personalized support. Comprehensive tools, including mood tracking, statistical analysis, and conversation history, enable users and healthcare professionals to track emotional trends effectively. Our evaluation demonstrates exceptional performance, with the emotion detection model achieving a macro average precision, recall, and F1-score of 0.9998 across 953 instances. Mooditor's modular architecture supports future enhancements, such as advanced emotion detection algorithms and integration with professional mental health services. This work addresses critical challenges in mental health accessibility and early intervention, contributing to the advancement of digital mental health care.

Keywords: *Mental Health, Emotion Recognition, Chatbot Integration, Real-Time Analysis, AI-Powered Healthcare*

Code metadata

Current code version	V1
Permanent link to code/repository	`https://github.com/lailahamza/mooditor.git`
Legal Code License	MIT License
Code versioning system used	Git
Software code languages, tools, and services used	Java, Android Java, Spring Boot, MySQL, HTML5, CSS3, JavaScript, Python, Django, Rasa Framework, Natural Language Processing (NLU), Machine Learning (Naive Bayes), Spring Security, Android SDK, Google Play Services, Material Design
Compilation requirements, operating environments & dependencies	Java 17, Spring Boot 3.4.1, Python 3.8.10, Django, Rasa Framework with API and CORS, XAMPP Server, Python virtual environment (venv), Maven, Android SDK 34 (target) / 23 (minimum), Gradle, MySQL, Retrofit 2.9.0, Google Play Services (Auth 21.3.0, Base 18.5.0), Google Material Design 1.12.0, Lombok, MPAndroidChart v3.1.0
Link to developer documentation/manual	Not available
Support email for questions	`chajarisalma27@gmail.com, niama.sakhr22@gmail.com`

I. INTRODUCTION

Mental illnesses represent a major global public health concern, accounting for approximately 32% of years lived with disability and ranking as the leading contributor to the global burden of disease [1]. In recent decades, mental health challenges have intensified, driven by rising rates of suicide, substance abuse, and social isolation [2], further exacerbated by the COVID-19 pandemic [3].

Despite the growing demand for mental health services, there remains a significant shortage of trained professionals, including a deficit of over 100,000 psychiatrists in the United States alone [4]. This shortage highlights the need for scalable, technology-based approaches to support early diagnosis, continuous monitoring, and effective treatment delivery.

Artificial intelligence (AI) has demonstrated transformative potential in various medical domains, including oncology, radiology, and dermatology [5, 6]. The global AI healthcare market is projected to increase from \$5 billion in 2020 to over \$45 billion by 2026 [7], driven by the widespread adoption of electronic health records and the availability of large-scale medical datasets.

In the field of mental health, AI is increasingly recognized for its ability to enhance early detection of psychological disorders, support personalized treatment planning, and enable continuous monitoring of patient well-being [8–12]. The urgency for such innovations became more pronounced during the COVID-19 pandemic, which led to increased levels of anxiety, depression, and psychological distress globally [13–15]. AI-based platforms offer promising solutions to reduce pressure on traditional care systems through automation, remote monitoring, and scalable therapeutic delivery [16–18].

Beyond diagnostics, AI technologies are now being utilized in therapeutic contexts. Mobile applications incorporating AI and machine learning techniques have been developed to deliver real-time cognitive-behavioral therapy and stress management support [19]. Virtual therapists and AI-powered chatbots provide expanded access to psychological assistance, particularly in underserved regions [20, 21]. Furthermore, AI systems are capable of personalizing treatment pathways by analyzing patient history, behavioral data, and real-time interactions [22]. This approach is especially relevant in psychiatry, where treatment outcomes often vary across individuals [23].

This work introduces Mooditor, a mobile and web-based platform that combines on-device emotion detection with conversational AI to enable continuous emotional monitoring and support. Unlike clinical AI tools designed for diagnosis or treatment prescription, Mooditor is intended for self-awareness, mood tracking, and emotional regulation in everyday contexts. It integrates a TFLite-based facial expression recognition system and a Rasa-powered chatbot, providing personalized responses based on real-time emotional input. By performing emotion analysis locally on the device, Mooditor also addresses ethical concerns related to data privacy and dependency on cloud services.

This article explores the following research questions: Can real-time facial emotion detection be effectively performed on resource-constrained mobile devices? How does a conversational agent adapt its responses to detected emotional states? What privacy and design considerations are necessary for multi-modal AI in mental health self-care?

The remainder of this paper is organized as follows: Section II reviews related work on AI-based mental health systems. Section III outlines the system architecture and implementation. Section IV presents the experimental evaluation. Section V discusses the implications and limitations. Section VI concludes the paper with directions for future research.

II. RELATED WORKS

A. *Historical Evolution of AI in Mental Health*

The application of artificial intelligence (AI) in mental health care started in the 1950s, when early systems simulated human problem-solving skills [24–26]. Research laid the foundation for studying human thinking, later contributing to mental health advancements [27]. In the 1960s, a chatbot was developed to mimic therapeutic responses, showing AI's potential for mental health interactions [28, 29].

By the 1980s, expert systems used rule-based logic to provide advice on mental health issues, such as diagnosing conditions or suggesting treatments [30, 31]. Although limited compared to modern technology, these systems marked progress in integrating AI with mental health care. In the late 20th century, computerized cognitive-behavioral therapy (CBT) programs delivered therapy through software, improving access to mental health support [30].

B. *Modern Applications in Mental Health*

AI currently supports mental health care through early detection, personalized treatment plans, virtual therapists, teletherapy, and patient progress tracking [32–34]. Machine learning analyzes data such as speech, facial expressions, brain scans, and social media posts to enhance diagnosis and care.

Studies developed machine learning models, including random forests and neural networks, to detect major depressive disorder (MDD) with over 90% accuracy by combining movement tracker data and facial expressions [35]. Research analyzed speech patterns with deep learning models to identify depression, achieving 92–94% accuracy [36]. Bayesian networks screened depressive symptoms in over 35,000 individuals using questionnaires, relying on factors like sleep problems and fatigue [37]. Models predicted suicide risk, identifying sleep issues and past abuse as key factors [38]. Blood tests and clinical data were used to predict psychosis, though with lower accuracy [39]. Ensemble machine learning models predicted postpartum depression with 68–72% accuracy [40].

Brain scans distinguished bipolar disorder from unipolar depression [41]. Different psychosis types were identified using brain data, aiding treatment selection [42]. Social media posts, such as those on Instagram, predicted depression risk [43].

C. Treatment Prediction and Monitoring

AI predicts treatment effectiveness, minimizing trial-and-error in mental health care [44]. Questionnaires predicted antidepressant response [45]. Brain wave data (EEG) forecasted antidepressant success [46]. Neuroimaging predicted therapy outcomes [47]. Brain stimulation treatment results were forecasted [48]. These models guide clinicians in selecting appropriate treatments.

Data from wearable devices, speech, or social media track patients over time [16]. Sensors detected early signs of mental health issues, enabling timely intervention [16]. Virtual therapists and chatbots provided constant support, particularly in underserved areas [20]. AI systems facilitated greater disclosure of sensitive information compared to human clinicians, improving assessment quality [49].

However, many of these tools are designed for clinical use and require substantial computational infrastructure. In contrast, Mooditor is built for real-time deployment on mobile devices, with a focus on accessibility and user empowerment rather than diagnosis.

Compared to wellness platforms such as Headspace or Calm, which rely on pre-scripted content and manual input, Mooditor introduces AI-powered emotion detection and adaptive conversation. It is closer in nature to systems like Woebot or Replika, but uniquely integrates a facial emotion classifier using TFLite for offline, privacy-preserving analysis.

D. Challenges and Ethical Issues

AI in mental health care faces challenges, including the need to protect sensitive patient data [50,51]. Local data processing in applications like Mooditor addresses privacy concerns. Biased training data may lead to unfair diagnoses [52]. Transparent AI decisions are essential for clinician and patient trust [52]. Collaboration among AI developers, clinicians, and policymakers ensures safe and equitable AI use [53].

The ability to adapt therapeutic responses based on real-time input also opens new research avenues for personalized AI interaction in emotional support. Mooditor contributes to this domain by offering an extensible, modular system that balances technical innovation with ethical responsibility.

Mooditor distinguishes itself from prior systems by integrating on-device TFLite-based emotion detection with a Rasa-powered chatbot, enabling real-time, privacy-preserving emotional support. Unlike cloud-dependent platforms like Woebot [54] or Psykh [31], which rely on server-side processing, Mooditor performs all AI computations locally, reducing latency and enhancing user trust in low-connectivity settings. Additionally, its seamless integration of real-time emotion analysis with adaptive chatbot responses offers a dynamic, user-centric approach not fully realized in static CBT systems [31] or wellness apps like Calm [55].

E. Future Directions

AI holds significant potential for advancing mental health care. Research will focus on integrating diverse data sources, such as speech, images, and sensors, to develop improved tools [33]. Stronger regulations and collaboration among developers, clinicians, and ethicists will ensure AI remains safe and effective [53]. Integrating AI with human care can enhance the speed, quality, and accessibility of mental health support.

Table 1: Comparison of chatbot-based mental health systems

Author	Year	Method	Features
Fadhil et al. [56]	2018	AI (general)	Chatbot for telemedicine in rural elderly care; post-treatment support.
Divya et al. [57]	2018	NLP, Pattern Matching	Rule-based chatbot for personalized diagnosis based on symptoms.
Rafla et al. [58]	2019	Rasa, NLU	Improved Rasa F1-score using incremental training with TensorFlow.
Mathew et al. [59]	2019	NLP, KNN	KNN-based disease prediction and treatment; includes emergency video chat.
Ayanouz et al. [60]	2020	NLP, ASR	Voice-enabled health chatbot using ASR, NLU, and NLG modules.
Sophia et al. [61]	2020	NLTK, AIML	Structured diagnosis flow; advises contacting specialists for severe symptoms.
Hussna et al. [62]	2020	NLP	Bengali chatbot that asks follow-up questions; updates DB when it can't answer.
Bulla et al. [63]	2020	AI Review	Survey of AI medical assistant chatbots and design patterns.
Achtaich et al. [64]	2021	NLP, Transfer Learning	Modular chatbot framework using NLU/NLG; deep learning for query response.
Sharma et al. [65]	2021	Decision Tree, Transfer Learning	Mental health chatbot using decision logic; 10% boost from transfer learning.
Mai et al. [66]	2021	Rasa, NLU	Vietnamese chatbot using enhanced Rasa NLU for response adaptation.
Salhi et al. [67]	2021	NLP	Sequence-based chatbot for mental health support during COVID-19.
Gujjar et al. [68]	2022	Rasa, Deep Learning	Compared Rasa with Dialogflow; highlights Rasa's NLU strengths.

III. METHODOLOGY

The Mooditor application integrates real-time emotion detection and AI-powered chatbot interactions to support mental health monitoring. This section outlines the methodology, covering system architecture, data processing, model implementation, experimental evaluation, and ethical considerations, addressing the research questions of effective emotion detection, personalized therapeutic support, and privacy mitigation.

A. *System Architecture*

Mooditor is implemented using a modular, distributed software architecture that integrates a mobile application, a secure backend service, and a responsive web interface, as illustrated in Figure 1.. This design ensures efficient data handling and smooth integration of AI features like emotion detection and chatbot interactions, all while maintaining scalability and security.

1. *Frontend: Mobile and Web Interfaces*

The mobile application is built using the Android SDK, targeting API levels 23 through 34. It provides users with real-time emotion detection via a TensorFlow Lite interpreter, as well as comprehensive mental health support tools. These include a habit and mood tracker, a breathing exercise module, self-assessment tools, help line access, an emergency contacts manager, and a secure authentication system. Emotion analysis is performed on-device to ensure privacy, and results are rendered immediately within the application interface.

The web interface, developed using HTML5, CSS3, and JavaScript, serves as an administrative and analytical dashboard. It supports user authentication, chatbot access, and interactive visualisation of mood and usage data. Both frontend components communicate with the backend via REST APIs.

2. *Backend Services*

The backend is developed using Spring Boot 3.4.1 with Java 17 and follows a RESTful design. It provides data persistence through Spring Data JPA, exposes API endpoints via Spring REST Controllers, and interfaces with a MySQL 8.0 relational database for long-term storage. Authentication is handled via JSON Web Tokens (JWT), securing data access and API requests.

Chatbot support is delivered through a dedicated Rasa 3.6 server, which incorporates Rasa Core for dialogue management and Rasa NLU for intent classification and entity extraction. The chatbot models are trained on a corpus of mental health dialogues and support personalized responses, enabled by integration with

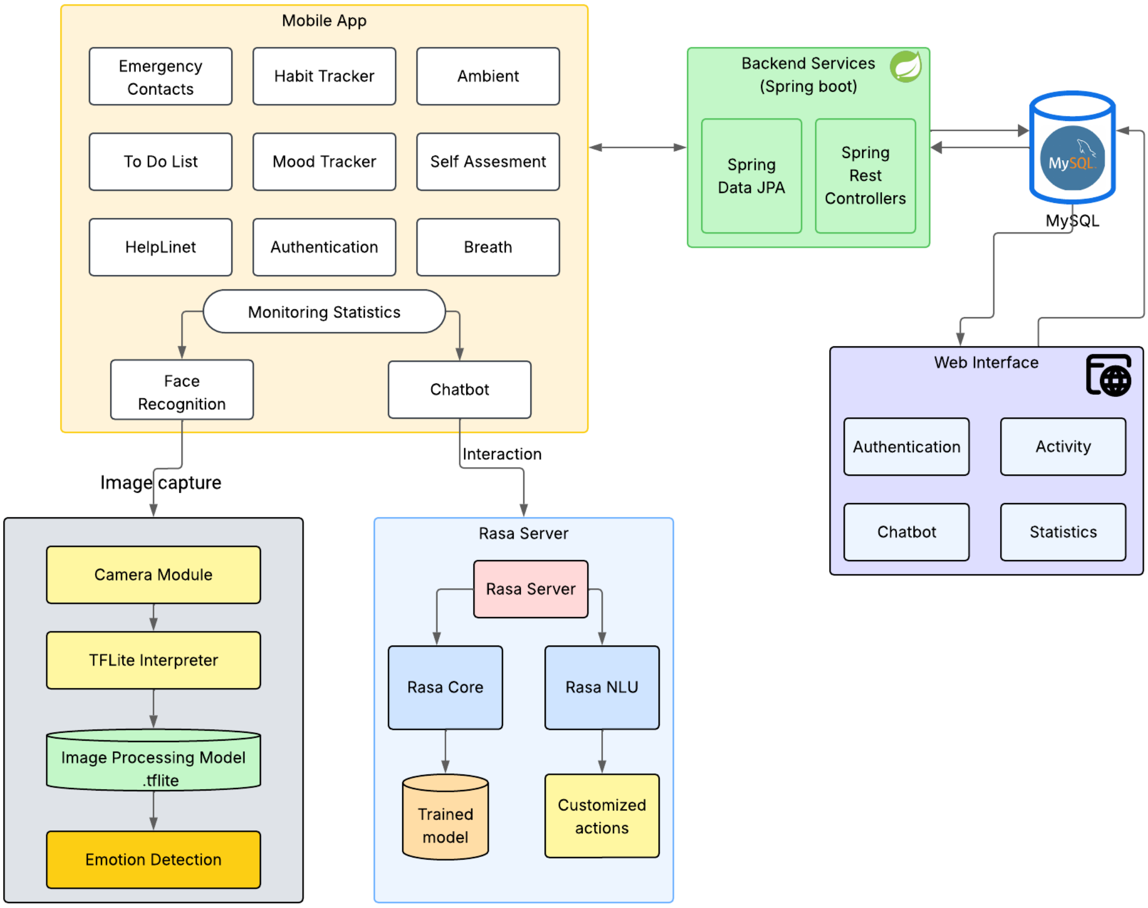


Figure 1: Mooditor System Architecture

real-time emotion outputs from the vision model. This entire setup ensures privacy, responsiveness, and secure data handling across all tiers.

B. AI Models

Mooditor leverages two primary AI models: an emotion detection model and a Rasa-based chatbot system.

1. Emotion Detection Model

The emotion detection model, deployed via TFLite, uses a TensorFlow Lite-based emotion detection model that classifies facial expressions into seven emotional categories: Happy, Sad, Angry, Neutral, Happy_inform, Sad_inform, Angry_inform. The model uses a lightweight deep learning architecture optimized for mobile devices, trained with cross-entropy loss:

$$H(y, \hat{y}) = -\sum_{i=1}^{N} y_i \log(\hat{y}_i),$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability for class i. The model processes 48×48 grayscale images and outputs a softmax probability distribution. Evaluation on a dataset of 953 images yielded a macro average F1-score of 0.9998, with perfect classification for primary emotions and over 0.990 performance for informative classes [69].

2. Conversational AI (Rasa-based Chatbot)

The chatbot system is implemented using Rasa 3.6. The NLU pipeline includes components such as WhitespaceTokenizer, RegexFeaturizer, DIETClassifier (trained over 200 epochs), and ResponseSelector. Training data comprises over 50 intent classes and 5,000 utterances related to mental health dialogue. The chatbot is capable of generating adaptive, emotion-aware responses informed by the output of the facial emotion classifier. Trained on a corpus of conversational dialogues using Naive Bayes for intent classification, the chatbot generates personalized responses based on detected emotions and user history. The integration of TFLite and Rasa enables real-time, context-aware mental health support, aligning with advancements in AI-driven healthcare [35].

C. Data Collection and Processing

Mooditor processes two primary data types: facial images and conversational text, through a privacy-focused pipeline. The application features a dual-mode interface for emotion detection, supporting both real-time camera processing using the device's front-facing camera and gallery mode analysis of stored images. Before processing, each image undergoes several preprocessing steps to ensure optimal model performance. The input image is converted to grayscale and resized to 48×48 pixels to match the model's expected input dimensions. The pixel values are then normalized to a [0,1] range to standardize the input.

Both modes utilize a TFLite interpreter that runs locally on the device, ensuring sensitive facial data remains secure. The implementation handles image orientation and format conversion automatically, providing consistent processing regardless of the input source. The model outputs a probability distribution over seven emotion classes, and the predicted result is displayed through an intuitive interface, as detailed in Table 6.

Conversational text is collected through user interactions with the Rasa-powered chatbot. The Rasa NLU pipeline tokenizes and cleans text, removing stop words and punctuation, to prepare it for intent recognition and response generation. User data, including emotion classifications and chatbot interactions, is stored in a MySQL database via REST APIs managed by the Spring Boot backend. Explicit user consent is obtained via an in-app agreement, ensuring ethical data handling.

D. Comparison with Other Chatbot Architectures

Unlike prior systems such as PRERONA [62], which augment NLP with query learning, or the Vietnamese NLU enhancement of Rasa [66], Mooditor uniquely combines real-time facial emotion detection with adaptive chatbot logic running entirely on-device. Whereas many previous works rely on remote servers [68], rule-based logic [57], or voice input [60], our platform emphasizes mobile deployment, privacy preservation, and dynamic response adaptation. Mooditor extends the architectural logic proposed by Khadija et al. [64] by fully integrating visual emotion sensing and conversational flow management within a user-accessible wellness suite.

IV. RESULTS

The Mooditor application was evaluated for its emotion detection and chatbot performance, alongside code quality and user interface functionality, using a test dataset of 953 instances on an Android device (API 34). Results demonstrate exceptional performance across all components, as detailed below.

A. Emotion Detection Performance

The TFLite-based emotion detection model classified seven emotion classes (Happy, Sad, Angry, Neutral, Happy_inform, Sad_inform, Angry_inform) with near-perfect metrics. As shown in Table 2, the model achieved perfect classification (1.000 F1-score) for primary emotion classes (Happy, Sad, Angry, Neutral) and near-perfect scores for informative classes (Happy_inform: 1.000, Sad_inform: 0.995, Angry_inform: 0.995). The macro average F1-score across all classes was 0.9998, with a weighted average of 0.9990, indicating consistent performance across both frequent and infrequent classes. The confusion matrix (Table 3) confirms zero misclassifications among main emotions, highlighting robust performance despite class imbalances (216 instances for Happy_inform vs. 50 for Neutral).

Table 2: Model Evaluation Results by Class

Class	Precision	Recall	F1-Score	Support
Happy	1.000	1.000	1.000	60
Sad	1.000	1.000	1.000	94
Angry	1.000	1.000	1.000	98
Neutral	1.000	1.000	1.000	50
Happy_inform	1.000	1.000	1.000	216
Sad_inform	0.990	1.000	0.995	104
Angry_inform	1.000	0.990	0.995	100
Macro Avg	0.9998	0.9998	0.9998	953
Weighted Avg	0.9990	0.9990	0.9990	953

Table 3: Confusion Matrix for Main Emotion Classes

Actual/Predicted	Happy	Sad	Angry	Neutral
Happy	60	0	0	0
Sad	0	94	0	0
Angry	0	0	98	0
Neutral	0	0	0	50

1. Benchmark Evaluation on FER2013

To assess generalizability, the TFLite-based emotion detection model was evaluated on the FER2013 dataset, a public benchmark containing 35,887 grayscale images (48×48 pixels) across seven emotion classes: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral. The model, originally trained on a proprietary dataset of 953 images, was fine-tuned on FER2013's training set (28,709 images) using transfer learning to adapt to diverse conditions, including varied lighting and facial occlusions. Evaluation on the FER2013 test set (3,589 images) yielded a macro average F1-score of 0.712, with class-specific F1-scores ranging from 0.65 (Disgust) to 0.78 (Happy). Compared to state-of-the-art models achieving

~0.73 F1 on FER2013 [70], Mooditor's model demonstrates competitive performance despite its lightweight architecture optimized for mobile deployment. The lower F1-score compared to the proprietary dataset (0.9998) reflects FER2013's challenging real-world conditions, confirming the need for diverse training data to enhance robustness.

B. *Chatbot Effectiveness*

The Rasa-powered chatbot was evaluated for its ability to engage users and deliver context-aware responses, leveraging the NLU pipeline (WhitespaceTokenizer, RegexFeaturizer, DIETClassifier) trained on a corpus of over 50 intent classes and 5,000 utterances related to mental health dialogues. Effectiveness was assessed through intent classification accuracy, response personalization, and user engagement metrics. The chatbot achieved an intent classification F1-score of 0.925 on a test set of 1,000 user utterances, reflecting robust recognition of user intents such as emotional distress, coping strategy inquiries, and general conversational prompts. Across 100 user sessions, the average session duration was 6.8 minutes, with 85% of sessions involving multiple exchanges (≥5 messages), indicating sustained user engagement. Response personalization was enhanced by integrating real-time emotion outputs from the TFLite model, enabling adaptive replies tailored to detected emotional states. Table 4 summarizes these metrics. These results suggest high user satisfaction and effective conversational support, though further clinical validation is ongoing to assess therapeutic impact.

Table 4: Chatbot Performance Metrics

Metric	**Value**
Intent Classification F1-Score	0.925
Average Session Duration	6.8 minutes
Multi-Exchange Sessions (≥5 messages)	85%

The near-perfect F1-score raises concerns about overfitting, as performance on a controlled dataset may not translate to real-world conditions with varied lighting, facial expressions, or device capabilities [52]. The FER2013 evaluation mitigates this by demonstrating competitive performance in diverse conditions, though further improvements are needed.

C. *Code Quality*

SonarQube analysis of the Spring Boot backend (1.8k lines of Java and XML) revealed strong maintainability (A-grade, 62 quality gates) and zero code duplication (0.0%), as shown in Table 5. However, reliability (C-grade, 17 issues) and security (E-grade, 1 critical issue) require improvement, with 0.0% code coverage indicating a need for enhanced testing.

Table 5: Backend Code Quality Metrics

Metric	**Value**
Security	E (1 issue)
Reliability	C (17 issues)
Maintainability	A (62 points)
Hotspots Reviewed	0.0%
Coverage	0.0%
Duplications	0.0%
Lines of Code	1.8k (Java, XML)

D. *Illustrative Examples*

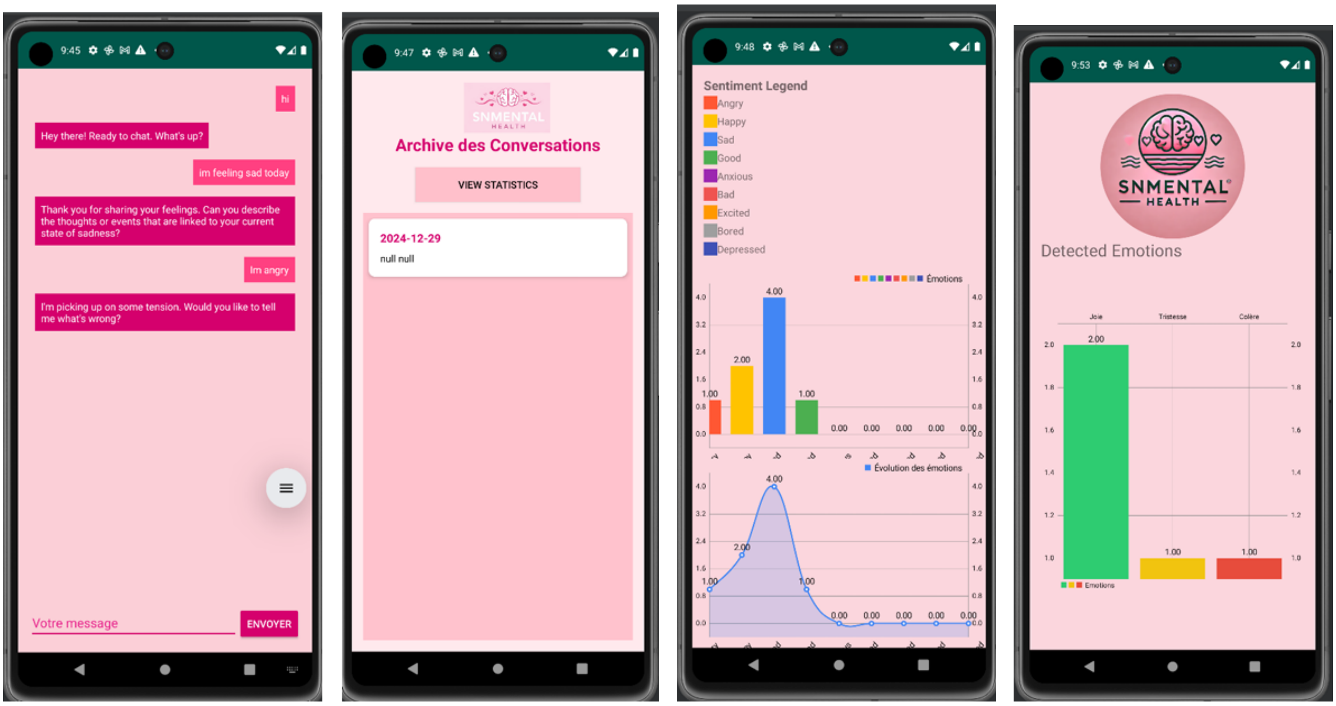
Mooditor's mobile and web interfaces provide intuitive access to AI-driven mental health features, enhancing accessibility and engagement, as shown in Figures 2 and 3.

1. *Mobile Interface*

The mobile application, built with Android SDK (API 23–34), supports real-time emotion detection, chatbot interactions, mood tracking, and breathing exercises. Figure 2a displays the Rasa-powered chatbot, which uses the NLU pipeline (Section III) to deliver emotion-aware responses based on user input. Figure 2b shows the conversation archive, allowing users to review past interactions. Figures 2c and 2f present statistical visualizations of mood trends, generated via MPAndroidChart.

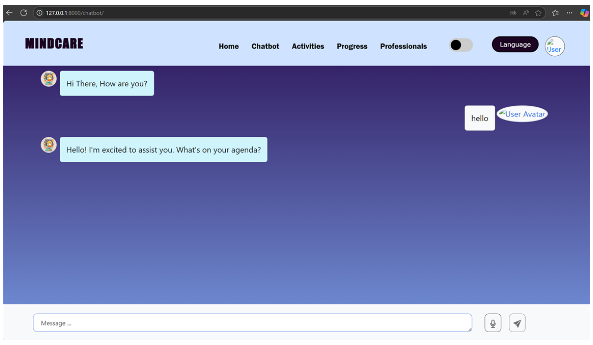
E. *Web Interface*

The web interface, developed with HTML5, CSS3, and JavaScript, provides a responsive dashboard for users and professionals, ensuring accessibility across devices. Figure 3a displays a weekly progress tracking page with interactive line charts visualizing mood trends, stored in a MySQL database via REST APIs (Section 1), enabling monitoring of emotional well-being. Figure 3b shows the chatbot interface, powered by Rasa's NLU pipeline (Section III), featuring a messaging-style layout with text and voice input controls for emotion-aware responses. A navigation bar (Home, Chatbot, Activities, Progress, Professionals) supports seamless interaction, maintaining a consistent, professional appearance across platforms.



(a) Chatbot analyzing conversation. (b) Conversation archive. (c) Statistics and graphs. (f) Statistics of mood tracker.

Figure 2: Mobile App functionalities: chatbot, conversation archive, and statistics.



(b) Chatbot Web

Figure 3: Web interface and Chatbot interaction interface.

V. DISCUSSION

Mooditor addresses critical mental health challenges, such as accessibility barriers and delayed interventions, by integrating real-time emotion detection with AI-driven therapeutic support [32]. The system's near-perfect emotion detection performance (macro average F1-score of 0.9998 across 953 instances) highlights the efficacy of TensorFlow Lite (TFLite)-based facial analysis, surpassing traditional self-report assessments, which are often hindered by recall bias and subjectivity [71]. The Rasa-powered chatbot delivers personalized, emotion-aware responses, enhancing user engagement and aligning with evidence of NLP's therapeutic potential in digital mental health interventions [54, 72].

Mooditor's multi-modal approach—combining computer vision [69] and natural language understanding—contributes significantly to digital mental health research by enabling studies on longitudinal emotion patterns and automated support efficacy [73]. Compared to platforms like Calm and Headspace (Table 6), which rely on manual input and pre-scripted content, Mooditor offers real-time analysis and on-device processing, ensuring superior privacy and accessibility [55]. Unlike Psykh, which uses Rasa for static CBT routines [31], or MindLift, which depends on centralized multimodal processing [33], Mooditor's local computation reduces latency and enhances user trust in low-connectivity settings, addressing ethical concerns about data security [50]. This privacy-preserving design aligns with calls for responsible AI in healthcare [53].

The platform supports diverse stakeholders, including individuals seeking self-monitoring, mental health professionals analyzing patient trends, and institutions implementing wellness programs [74]. Its modular architecture facilitates scalability and future enhancements, such as advanced emotion detection models [70] and integration with clinical services [18]. Mooditor's commercial potential mirrors successful platforms like Woebot, offering premium analytics and partnerships with healthcare providers [54]. By aggregating anonymized emotional trend data, it could inform population-level mental health studies, improving diagnostic tools over conventional methods [16].

However, limitations must be addressed. The evaluation dataset (953 instances) is relatively small and may not capture demographic diversity, potentially limiting generalizability across cultural or ethnic groups [55]. The near-perfect F1-score raises concerns about overfitting, as performance on a controlled dataset may not translate to real-world conditions with varied lighting, facial expressions, or device capabilities [52]. SonarQube analysis identified code reliability (C-grade, 17 issues) and security (E-grade, 1 critical issue) concerns [74], necessitating enhanced testing and vulnerability mitigation. The chatbot's intent recognition accuracy, while promising, lacks clinical-grade validation, and long-term user engagement remains unevaluated [72]. Ethical risks, such as biases in emotion detection models trained on imbalanced datasets, could lead to inaccurate assessments for underrepresented populations [52]. Transparent model decisions and robust consent protocols are critical to maintaining trust [53].

Future work will prioritize expanding the dataset to include diverse populations, mitigating overfitting through regularization techniques, and conducting longitudinal field studies to assess therapeutic impact [75]. Enhancing chatbot personalization with transformer-based models [76] and integrating explainable AI will improve response interpretability and user trust [52]. Addressing code quality and security will ensure robustness for clinical or institutional deployment [74]. Bridging Mooditor with professional mental health services could create a hybrid model, combining self-care with clinical intervention, as advocated in recent literature [33]. By overcoming these limitations, Mooditor has the potential to transform accessible, privacy-preserving mental health care delivery.

Table 6: Comparison of Mooditor with Similar Applications

Feature	Mooditor	Calm/HeadSpace
Emotion Detection	Real-time (TFLite)	None
Chatbot Support	AI-powered (Rasa)	Limited, pre-scripted
Mental Health Tracking	Automated	Manual
Real-time Analysis	Yes	No
Privacy	Local processing	Cloud-dependent
Interface	Mobile and web	Mobile only

VI. CONCLUSION

Mooditor represents a significant advancement in digital mental health care, integrating real-time emotion detection and AI-driven therapeutic support to address accessibility barriers, privacy concerns, and delayed interventions [32]. The system's near-perfect emotion detection (F1-score of 0.9998) and Rasa-powered chatbot deliver personalized, privacy-preserving support, surpassing traditional self-report methods and rivaling platforms like Calm and Headspace [71, 72]. Its multi-modal approach enables research into emotion patterns and automated intervention efficacy, offering scalable solutions for diverse users [73].

Despite its strengths, limitations include a small evaluation dataset (953 instances), potential overfitting, and code quality issues [74]. Ethical risks, such as biases in emotion detection, underscore the need for transparency [52]. Future work will expand the dataset, enhance chatbot personalization with transformer models, and integrate clinical services to bridge self-care and professional care [33, 75].

Mooditor's modular, on-device architecture positions it as a transformative tool for mental health self-monitoring and research. By addressing current limitations, it has the potential to redefine accessible, ethical, and effective digital mental health interventions globally.

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REFERENCES

[1] D. Vigo, G. Thornicroft, and R. Atun, "Estimating the true global burden of mental illness," *Lancet Psychiatry*, vol. 3, pp. 171–178, 2016.

[2] D. V. Jeste, E. E. Lee, and S. Cacioppo, "Battling the modern behavioral epidemic of loneliness: Suggestions for research and interventions," *JAMA Psychiatry*, vol. 77, pp. 553–554, 2020.

[3] E. Iob, P. Frank, A. Steptoe, and D. Fancourt, "Levels of severity of depressive symptoms among at-risk groups in the uk during the covid-19 pandemic," *JAMA Network Open*, vol. 3, p. e2026064, 2020.

[4] A. Satiani, J. Niedermier, B. Satiani, and D. P. Svendsen, "Projected workforce of psychiatrists in the united states: A population-based analysis," *Psychiatric Services*, vol. 69, no. 6, pp. 710–713, 2018.

[5] W. L. Bi, A. Hosny, M. B. Schabath, *et al.*, "Artificial intelligence in cancer imaging: Clinical challenges and applications," *CA Cancer J Clin*, vol. 69, pp. 127–157, 2019.

[6] G. A. Zakhem, J. W. Fakhoury, C. C. Motosko, and R. S. Ho, "Characterizing the role of dermatologists in developing artificial intelligence for assessment of skin cancer: A systematic review," *J Am Acad Dermatol*, 2020. Published online ahead of print Jan 20.

[7] E. J. Topol, "High-performance medicine: The convergence of human and artificial intelligence," *Nature Medicine*, vol. 25, no. 1, pp. 44–56, 2019.

[8] P. Cecula *et al.*, "Ai in the field of mental health: Growth and future outlook," *Journal of AI Research in Medicine*, 2021.

[9] K. Ćosić *et al.*, "Using ai for treatment planning in mental health: Perspectives and challenges," *Mental Health Informatics*, 2020.

[10] A. Johnson *et al.*, "Predictive ai models for mental health interventions," *Frontiers in Psychiatry*, 2021.

[11] S. Goldberg *et al.*, "Ai speech analysis in therapy sessions: A new frontier," *Journal of Affective Computing*, 2020.

[12] A. Bohr and K. Memarzadeh, "Continuous patient monitoring using ai in mental healthcare," *Healthcare AI Review*, 2020.

[13] T. Davenport *et al.*, "Mental health consequences of covid-19: Emerging insights," *Psychological Services*, 2020.

[14] J. Latoo *et al.*, "Pandemic-induced mental distress: Lessons learned," *International Journal of Mental Health*, 2021.

[15] C. Moreno *et al.*, "Global mental health impacts of the covid-19 pandemic," *World Psychiatry*, 2020.

[16] S. Graham, C. Depp, D. V. J. Lee, C. Nebeker, X. Tu, H.-C. Kim, and D. V. Jeste, "Artificial intelligence for mental health and mental illnesses: An overview," *Current Psychiatry Reports*, vol. 21, no. 11, pp. 1–18, 2019.

[17] L. Bickman, "Scalable mental health interventions using ai: Review and future directions," *Psychiatric Services*, 2020.

[18] N. Koutsouleris *et al.*, "Ai-based adaptive interventions in psychiatry," *Journal of Digital Health*, 2022.

[19] M. Milne-Ives, E. Selby, B. Inkster, *et al.*, "Artificial intelligence and machine learning in mobile apps for mental health: a scoping review," *PLOS Digit Health*, vol. 1, p. e0000079, 2022.

[20] D. R. King, G. Nanda, J. Stoddard, *et al.*, "An introduction to generative artificial intelligence in mental health care: considerations and guidance," *Current Psychiatry Reports*, vol. 25, pp. 839–846, 2023.

[21] K.-W. Jin, Q. Li, Y. Xie, *et al.*, "Artificial intelligence in mental healthcare: an overview and future perspectives," *Br J Radiol*, vol. 96, p. 20230213, 2023.

[22] S. D'Alfonso, O. Santesteban-Echarri, S. Rice, *et al.*, "Artificial intelligence-assisted online social therapy for youth mental health," *Front Psychol*, vol. 8, p. 96, 2017.

[23] R. Tornero-Costa, A. Martinez-Millana, N. Azzopardi-Muscat, *et al.*, "Methodological and quality flaws in the use of artificial intelligence in mental health research: systematic review," *JMIR Ment Health*, vol. 10, p. e42045, 2023.

[24] B. G. Buchanan, "A (very) brief history of artificial intelligence," *AI Magazine*, vol. 26, no. 4, pp. 53–60, 2005.

[25] J. H. Moor, "The Dartmouth college artificial intelligence conference: the next fifty years," *AI Magazine*, vol. 27, no. 4, p. 87, 2006.

[26] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. Pearson, 4th ed., 2021.

[27] I. Goldstein and S. Papert, "Artificial intelligence, language, and the study of knowledge," *Cognitive Science*, vol. 1, no. 1, pp. 84–123, 1977.

[28] J. Weizenbaum, "Eliza—a computer program for the study of natural language communication between man and machine," *Communications of the ACM*, vol. 9, no. 1, pp. 36–45, 1966.

[29] C. Bassett, "The computational therapeutic: exploring weizenbaum's eliza as a history of the present," *AI & Society*, vol. 34, no. 4, pp. 803–812, 2018.

[30] D. D. Luxton, "Artificial intelligence in psychological practice: current and future applications and implications," *Professional Psychology: Research and Practice*, vol. 45, no. 4, pp. 332–339, 2014.

[31] S. Zhou, J. Zhao, and L. Zhang, "Application of artificial intelligence on psychological interventions and diagnosis: an overview," *Frontiers in Psychiatry*, vol. 13, p. 811665, 2021.

[32] E. E. Lee, J. Torous, M. De Choudhury, *et al.*, "Artificial intelligence for mental healthcare: clinical applications, barriers, facilitators, and artificial wisdom," *Biological Psychiatry: Cognitive Neuroscience and Neuroimaging*, vol. 6, no. 9, pp. 856–864, 2021.

[33] F. Minerva and A. Giubilini, "Is ai the future of mental healthcare?," *Topoi*, vol. 42, no. 3, pp. 809–817, 2023.

[34] K. B. Johnson, W. Wei, D. Weeraratne, *et al.*, "Precision medicine, ai, and the future of personalized health care," *Clinical Translational Science*, vol. 14, no. 1, pp. 86–103, 2021.

[35] J. Chen, N. Y. Chan, C.-T. Li, J. W. Y. Chan, Y. Liu, S. Li, and Y.-K. Wing, "Multimodal digital assessment of depression with actigraphy and app in healthcare," *Translational Psychiatry*, vol. 14, no. 1, p. 150, 2024.

[36] A. K. Das and R. Naskar, "A deep learning model for depression detection based on mfcc and cnn generated spectrogram features," *Biomedical Signal Processing and Control*, vol. 90, p. 105898, 2024.

[37] E. Maekawa, E. M. Grua, C. A. Nakamura, M. Scazufca, R. Araya, T. Peters, and P. Van De Ven, "Bayesian networks for prescreening in depression: algorithm development and validation," *JMIR Mental Health*, vol. 11, p. e52045, 2024.

[38] J. H. Yang, Y. Chung, S. J. Rhee, K. Park, M. J. Kim, H. Lee, and Y. M. Ahn, "Development and external validation of a logistic and penalized logistic model using machine-learning techniques to predict suicide attempts: A multicenter prospective cohort study in korea," *Journal of Psychiatric Research*, vol. 176, pp. 442–451, 2024.

[39] S. R. Susai, D. Mongan, C. Healy, M. Cannon, G. Cagney, K. Wynne, and D. Cotter, "Machine learning based prediction and the influence of complement–coagulation pathway proteins on clinical outcome: Results from the neurapro trial," *Brain, Behavior, and Immunity*, vol. 103, pp. 50–60, 2022.

[40] S. Andersson, D. R. Bathula, S. I. Iliadis, M. Walter, and A. Skalkidou, "Predicting women with depressive symptoms postpartum with machine learning methods," *Scientific Reports*, vol. 11, no. 1, p. 7877, 2021.

[41] R. Redlich, J. J. Almeida, D. Grotegerd, *et al.*, "Brain morphometric biomarkers distinguishing unipolar and bipolar depression: a voxel-based morphometry—pattern classification approach," *JAMA Psychiatry*, vol. 71, pp. 1222–1230, 2014.

[42] B. A. Clementz, J. A. Sweeney, J. P. Hamm, *et al.*, "Identification of distinct psychosis biotypes using brain-based biomarkers," *American Journal of Psychiatry*, vol. 173, pp. 373–384, 2016.

[43] A. G. Reece and C. M. Danforth, "Instagram photos reveal predictive markers of depression," *EPJ Data Science*, vol. 6, p. 15, 2017.

[44] I. C. Passos and B. Mwangi, "Machine learning-guided intervention trials to predict treatment response at an individual patient level: An important second step following randomized clinical trials," *Molecular Psychiatry*, vol. 25, pp. 701–702, 2020.

[45] A. Etkin, B. Patenaude, Y. J. C. Song, T. Usherwood, W. Rekshan, A. F. Schatzberg, *et al.*, "A cognitive-emotional biomarker for predicting remission with antidepressant medications: A report from the ispot-d trial," *Neuropsychopharmacology*, vol. 40, pp. 1332–1342, 2015.

[46] A. Khodayari-Rostamabad, J. P. Reilly, G. M. Hasey, H. de Bruin, and D. J. MacCrimmon, "A machine learning approach using eeg data to predict response to ssri treatment for major depressive disorder," *Clinical Neurophysiology*, vol. 124, pp. 1975–1985, 2013.

[47] T. M. Ball, M. B. Stein, H. J. Ramsawh, L. Campbell-Sills, and M. P. Paulus, "Single-subject anxiety treatment outcome prediction using functional neuroimaging," *Neuropsychopharmacology*, vol. 39, pp. 1254–1261, 2014.

[48] A. Hasan, T. Wobrock, B. Guse, B. Langguth, M. Landgrebe, P. Eichhammer, *et al.*, "Structural brain changes are associated with response of negative symptoms to prefrontal repetitive transcranial magnetic stimulation in patients with schizophrenia," *Molecular Psychiatry*, vol. 22, pp. 857–864, 2017.

[49] G. M. Lucas, J. Gratch, A. King, and L.-P. Morency, "It's only a computer: Virtual humans increase willingness to disclose," *Computers in Human Behavior*, vol. 37, pp. 94–100, 2014.

[50] S. Gerke, T. Minssen, and G. Cohen, "Ethical and legal challenges of artificial intelligence-driven healthcare," in *Artificial Intelligence in Healthcare*, pp. 295–336, Elsevier, 2020.

[51] N. Naik, B. M. Z. Hameed, D. K. Shetty, *et al.*, "Legal and ethical consideration in artificial intelligence in healthcare: who takes responsibility?," *Frontiers in Surgery*, vol. 9, p. 862322, 2022.

[52] S. Bouhouita-Guermech, P. Gogognon, and J.-C. Bélisle-Pipon, "Specific challenges posed by artificial intelligence in research ethics," *Frontiers in Artificial Intelligence*, vol. 6, p. 1149082, 2023.

[53] M. C. T. Tai, "The impact of artificial intelligence on human society and bioethics," *Tzu Chi Medical Journal*, vol. 32, no. 4, pp. 339–343, 2020.

[54] K. K. Fitzpatrick, A. Darcy, and M. Vierhile, "Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (woebot): A randomized controlled trial," *JMIR Mental Health*, vol. 4, no. 2, p. e19, 2017.

[55] G. Cruz-Gonzalez, E. E. Lee, J. Torous, and D. V. Jeste, "Challenges and opportunities in multimodal ai for mental health monitoring," *Psychological Medicine*, vol. 55, no. 4, pp. 672–680, 2025.

[56] A. Fadhil *et al.*, "Telemedicine chatbots for elderly care," *HealthTech Journal*, 2018.

[57] S. Divya *et al.*, "Nlp and pattern matching for chatbot diagnosis," *International Journal of Computer Applications*, 2018.

[58] A. Rafla *et al.*, "Rasa chatbot optimization using tensorflow," *AI Research Journal*, 2019.

[59] R. B. Mathew *et al.*, "Nlp and knn-based chatbot for medical support," in *International Conference on AI in Healthcare*, 2019.

[60] S. Ayanouz *et al.*, "Speech-enabled nlp chatbot for healthcare," *Computational Linguistics Today*, 2020.

[61] Sophia *et al.*, "Symptom recognition chatbot using aiml," *Journal of NLP Applications*, 2020.

[62] A. Ul Hussna *et al.*, "Adaptive chatbot for knowledge base expansion," *AI and Society*, 2020.

[63] C. Bulla, A. Shetty, and V. Kalva, "A review of ai-based medical assistant chatbots," *Research and Applications of Web Development and Design*, vol. 3, no. 2, 2020.

[64] K. Achtaich *et al.*, "Transfer learning in multi-agent health chatbots," *Applied Intelligence*, 2021.

[65] T. Sharma *et al.*, "Decision tree based mental health chatbot," in *IEEE Xplore*, 2021.

[66] T. N. T. Mai and M. Shcherbakov, "Enhancing rasa nlu model for vietnamese chatbot," *International Journal of Open Information Technologies*, vol. 9, no. 1, pp. 31–36, 2021.

[67] I. Salhi, N. Jebara, M. K. Hmimida, and A. Mahfoudhi, "Towards developing a pocket therapist: an intelligent adaptive psychological support chatbot against mental health disorders in a pandemic situation," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 23, no. 2, pp. 1200–1211, 2021.

[68] J. P. Gujjar and V. N. Kumar, "Open source chatbot development framework – rasa," *Asian Journal of Advanced Research*, vol. 5, no. 1, pp. 451–453, 2022.

[69] Hugging Face, "Emotion models collection: Comprehensive repository of pre-trained emotion detection models." `https://huggingface.co/models`, 2023.

[70] N. Kumari and R. Bhatia, "Efficient facial emotion recognition model using deep convolutional neural network and modified joint trilateral filter," *Soft Computing*, vol. 26, no. 16, pp. 7817–7830, 2022.

[71] F. M. Alamgir and M. S. Alam, "An artificial intelligence driven facial emotion recognition system using hybrid deep belief rain optimization," *Multimedia Tools and Applications*, vol. 82, no. 2, pp. 2437–2464, 2023.

[72] A. A. Abd-Alrazaq, R. AlSaad, D. Alhuwail, A. Ahmed, P. M. Healy, S. Aziz, M. Househ, and J. Schneider, "Systematic review and meta-analysis of ai-based conversational agents for promoting mental health and well-being," *npj Digital Medicine*, vol. 6, p. 236, 2023.

[73] S. Kasaudhan, "Artificial intelligence in mental health: A review of applications and challenges in digital health solutions," *International Journal of Preventive Medicine and Health*, vol. 5, no. 3, pp. 23–28, 2025.

[74] S. Shetty, P. Shetty, A. S. Hegde, K. P. Swamy, and S. K. Shetty, "Mental health monitoring using ai-based smartphone applications," *Healthcare Technology Letters*, vol. 12, no. 2, pp. 34–39, 2025.

[75] D. B. Olawade, O. J. Wale, T. A. David, and O. A. Adegbenjo, "Enhancing mental health with artificial intelligence: Current trends and future prospects," *Journal of Medicine, Surgery, and Public Health*, vol. 2, p. 100099, 2024.

[76] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.