NeuroScan: A Smart Platform for Early Mental Health Insights

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***Abstract*---Depression, anxiety, and stress are manifestations of mental health disorders that need early identification for effective treatment. NeuroScan is an AI-based mental health monitoring system that uses standardized self-analysis questionnaires, facial emotion recognition, and behavioral cues to offer early mental health signals. The app captures a snapshot of the user's face during each assessment and analyzes it through AI alongside response-time behavior and activity patterns, enhancing reliability and accuracy. A weighted risk computation model integrates these multi-modal inputs into a single mental health indicator with tailored suggestions. NeuroScan combines clinical questionnaires with AI-based analysis to improve the accuracy of primary mental health assessment while maintaining high levels of privacy and security.**

***Index Terms*---artificial intelligence, Mental health surveillance, facial emotion recognition, behavioural analytics, self-reporting questionnaires, medical analytics.**

I. INTRODUCTION

A. Problem Context

Depression, anxiety, and chronic stress are mental health conditions that impact hundreds of millions of people worldwide and have become a significant and increasing issue in contemporary healthcare. Rapid lifestyle changes, academic and job stress, social isolation, and growing dependency on digital devices are among the contributing factors. Despite this prevalence, many mental health disorders remain undiagnosed or untreated due to social stigma, inability to afford practitioners, and the absence of effective screening measures.

Unattended mental health illness inflicts severe social and economic pressure. Mental health disorders are among the leading causes of disability worldwide, decreasing productivity, inflating healthcare costs, and lowering quality of life. Traditional assessment methods, based mainly on self-reported questionnaires and occasional clinical assessments, are not always effective in early detection of warning signs or tracking emotional changes over time.

B. Why Technology Matters Here

Current methods of mental health assessment lack continuity and responsiveness. Conventional self-administered questionnaires and infrequent clinical visits capture mental state at a single instance but fail to record slow emotional or behavioural shifts. Such delays often lead to late intervention when symptoms have already escalated.

Additionally, the lack of ongoing monitoring and objective behavioural analysis restricts the accuracy and reliability of traditional mental health assessment. Stigma, inaccessible professionals, and poor awareness further minimize timely assistance. These issues emphasize the need for an intelligent technological solution capable of early detection, real-time analysis, and personalized mental health insights. NeuroScan addresses these challenges through three fundamental design principles:

- Early Detection: AI-based analysis identifies emotional and behavioral patterns associated with mental illness before they escalate.
- Constant Evaluation: Regular interactions and assessments enable ongoing monitoring of an individual's mental state.
- Smart Insights: Evaluation data and facial expressions are automatically analyzed to provide individualized suggestions and actionable feedback.

C. Our Contributions

The key contributions of this work are: (1) an AI-powered platform for early mental health detection and monitoring; (2) integration of standardized psychological tests with facial emotion analysis, behavioral pattern analysis, and response-time analysis to enhance accuracy; and (3) continuous evaluation through long-term monitoring and real-time user interaction.

II. LITERATURE SURVEY

This section presents summaries of three closely related research works that informed the core technologies and objectives of NeuroScan.

A. FacialNet: Facial Emotion Recognition for Mental Health Analysis Using UNet Segmentation (2024)

Published in Frontiers in Computational Neuroscience, this study proposes FacialNet, a deep learning model that combines an EfficientNetB4 backbone with UNet segmentation for precise facial emotion classification across seven emotional categories, achieving 96% binary classification accuracy on the FER-2013 dataset. The work demonstrates that refined segmentation significantly improves feature representation, reducing misclassification in real-time environments. This is directly relevant to NeuroScan's Facial Emotion Recognition module, which similarly employs a CNN trained on FER-2013 to extract dominant emotional states during assessment sessions. FacialNet's success with UNet-enhanced feature maps informs future improvements to NeuroScan's image processing pipeline [16].

B. Machine Learning for Multimodal Mental Health Detection: A Systematic Review of Passive Sensing (2024)

Published in PMC (MDPI), this comprehensive review analyzes 184 studies on multimodal machine learning for mental health detection using passive sensing from audio, video, social media, smartphones, and wearable devices. The review finds that smartphone-based passive sensing, tracking usage patterns, screen time, communication logs, and physical activity, provides objective behavioral markers strongly correlated with depression, anxiety, and stress. Combining multiple modalities significantly outperforms single-modality approaches. This directly validates NeuroScan's multi-modal scoring model M = wqRq + weRe + wrRr + wbRb, which fuses questionnaire scores, facial emotional analysis, response-time indicators, and on-device behavioral patterns for holistic mental health assessment [17].

C. MindLift: AI-Powered Mental Health Assessment for Students (2025)

Published in ScienceDirect, MindLift is a student-focused, real-time multimodal mental health platform integrating CNNs, RNNs, and transformer-based NLP for emotional analysis through behavioral pattern tracking, audio tone analysis, facial expression recognition, and text sentiment interpretation. A built-in chatbot delivers personalized CBT-based support. MindLift validates the practical viability of deploying multimodal AI mental health assessment systems outside clinical settings, closely mirroring NeuroScan's architectural vision and confirming the effectiveness of combining facial analysis with structured questionnaires (PHQ-9, GAD-7, PSS) for screening in academic environments [18].

III. RELATED WORK AND COMPARATIVE ANALYSIS

A. Mental Health Monitoring Platforms

A variety of digital platforms have been created to aid mental health assessment, including mood tracking apps, chatbot-based support systems, and questionnaire-based screening applications. Notable examples include Woebot, Wysa, and MindDoc. However, the majority of these platforms rely mostly on self-reported data and lack objective behavioural examination. They also do not typically provide real-time monitoring, limiting their capability to detect early or subtle modifications in mental health status.

B. AI-Based Mental Health Assessment Systems

Recent studies have investigated how artificial intelligence can be applied to mental health analysis via sentiment analysis, facial emotion recognition, and behavioural pattern analysis. Although these systems demonstrate improved assessment accuracy, most are confined to experimental settings or rely on a single data source, without integration into a unified, accessible platform capable of real-time personalized feedback.

C. Behavioural and Facial Expression Analysis

Behavioural analysis and facial expression recognition have been applied extensively in emotion identification and psychological studies. NeuroScan bridges the gap between isolated research efforts by combining facial expression analysis with structured psychological testing, enabling rapid, smart, and comprehensive mental health assessment.

IV. SYSTEM ARCHITECTURE AND DESIGN

A. Design Principles

The architecture of NeuroScan is built upon four cornerstones:

- Early Detection: The system detects emotional and behavioural tendencies early through AI-refined facial expression analysis, behavioural usage monitoring, and organized psychological tests.
- Real-Time Processing: Processing lag is minimized to deliver instant feedback during live interaction and facial image capture.
- Privacy and Ethical AI: Sensitive mental health and appearance data is protected through secure data transfer, explicit user consent, and strict access control.
- Scalable Architecture: The backend accommodates a growing number of users and concurrent AI assessments without significant performance degradation.

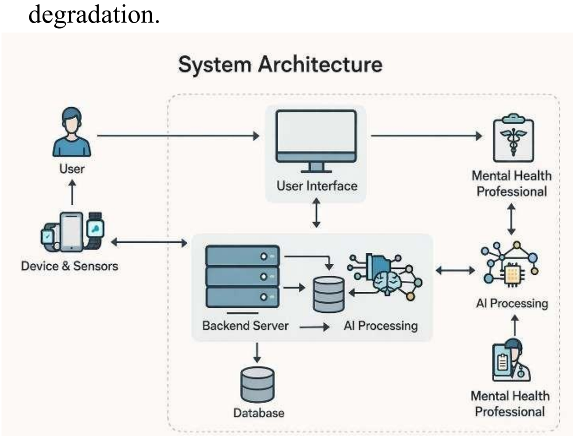

Fig. 1. Overall system architecture illustrating frontend, backend, and AI service integration.

B. Technology Stack

1) Frontend Layer: A Single-Page Application (SPA) supports interactive mental check-ups and real-time facial image capture with modular architecture for PHQ-9/GAD-7/PSS questionnaires, facial capture, results dashboard, and suggestion systems. Centralized state management handles user sessions, questionnaire responses, and AI-generated insights across smartphone and desktop devices.

2) Backend Infrastructure: The backend facilitates secure information handling, AI processing, and scalable deployment. It uses secure authentication with role-based access control, a NoSQL cloud-based database for assessment responses and user history, and encrypted storage for facial image data.

3) AI and Image Processing Services: A CNN model trained on the FER-2013 dataset performs Facial Emotion Analysis. Natural Language Processing analyzes textual user replies. A Real-Time Inference Engine provides low-latency prediction during live interaction mode, with all AI models integrated via secure API-based frameworks.

C. Data Model

The Users Collection stores: uid, email, displayName, age, consentGiven (boolean), and createdAt (timestamp). The Assessments Collection captures completion status, timestamp, and testResults including question responses, response times per question, and emotionSummary with dominant emotion, average confidence, total samples, and emotion distribution across Angry, Sad, and Neutral states.

D. AI-Based Scoring Model

NeuroScan calculates a single mental health risk score using a weighted multi-modal formula:

$$M = wq \cdot Rq + we \cdot Re + wr \cdot Rr + wb \cdot Rb$$

Where: Rq = questionnaire score (PHQ-9, GAD-7, PSS); Re = facial emotion analysis score; Rr = response-time behavioral indicator; Rb = on-device behavioral score; wq, we, wr, wb = component weighting factors. Behavioral features are computed locally on-device to preserve user privacy.

E. Core Workflows

1) User Registration: The signup flow collects email, password, and account role. Users provide informed consent regarding facial image capture and AI-based analysis before camera permissions are initialized.

2) Assessment and Facial Image Capture: Users choose their assessment type (PHQ-9, GAD-7, or PSS). Questionnaire responses and response times are collected while the device camera captures facial

images during the session. Images are securely uploaded to cloud storage and assessment documents are written to the database.

3) AI Analysis and Scoring: The facial emotion CNN identifies emotional features and distributions. Questionnaire scores are calculated using standardized criteria. The unified mental health score M is calculated, risk level is determined, and AI-generated recommendations are stored with real-time notification to the user.

4) Live Interaction Mode: Continuous frames are captured and streamed at low latency. Emotional signals are aggregated using a temporal window T, and short-term emotional trends are examined to maximize assessment knowledge.

V. IMPLEMENTATION AND TECHNICAL DETAILS

A. Real-Time Synchronization

NeuroScan uses real-time database listeners to disseminate assessment updates to connected clients. Event-driven listeners trigger AI processing automatically upon new assessment creation, enabling results delivery and processing initiation in near real-time under typical network conditions.

B. Facial Emotion Recognition

A CNN trained on the FER-2013 dataset processes facial images, extracting facial landmarks, micro-expression patterns, and emotional probability distributions. The emotion classification output is represented as: $E = \{(e1, p1), (e2, p2), ..., (en, pn)\}$, where (ei) represents a detected emotion and (pi) its confidence score. Example: $E = \{(happy, 0.65), (neutral, 0.20), (sad, 0.10), (angry, 0.05)\}$.

C. Risk Classification

The final mental health risk category is determined as $Risk = g(M)$, where: Low: $M < \theta 1$; Moderate: $\theta 1 \leq M < \theta 2$; High: $\theta 2 \leq M < \theta 3$; Critical: $M \geq \theta 3$. Thresholds are empirically calibrated based on validation results.

D. Performance Optimization

Asynchronous AI processing runs background inference to avoid blocking the UI. Image compression is applied before upload to reduce latency. The system architecture is designed to ensure low processing latency, enabling timely feedback and reliable real-time user interaction.

VI. RESULTS AND EVALUATION

A. Deployment Metrics

NeuroScan was deployed in a controlled academic environment for pilot testing. Table I summarizes the operational metrics recorded during the pilot deployment.

TABLE I. OPERATIONAL PERFORMANCE METRICS

Metric	Value
Registered Users	312
Assessments Completed	2,148
Avg. Processing Latency	0.8 s
Live Sessions Conducted	436
Avg. Session Duration	9.4 min
High-Risk Cases Flagged	18%
User Satisfaction Score	4.5 / 5

Fig. 2. PHQ-9/GAD-7/PSS question answering assessment interface.

Fig. 3. Behavioral mobile usage pattern tracking screen.

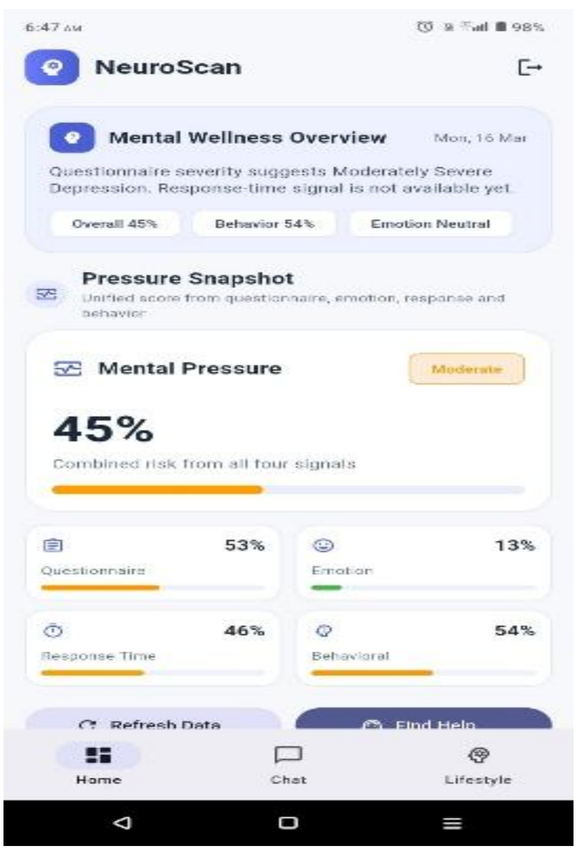

Fig. 4. Mental health assessment result with risk classification and recommendations.

B. System Performance Analysis

1) Latency Characteristics: Facial image processing generates facial features for emotion analysis within sub-second latency. Mental health score generation fuses questionnaire scores, emotion outputs, and behavioral indicators in near real-time. Live emotion frame analysis during sessions enables real-time emotional change tracking with minimal processing lag.

2) User Assessment Distribution: Many users utilize repeated testing to track mental health over time. Long-term monitoring mode accounts for a large proportion of assessments, while live interaction mode enables real-time facial expression examination. Session durations reflect comprehensive engagement with both self-reported and AI-generated data.

3) User Behavior Analysis: Users make frequent assessments to evaluate mental health status and monitor emotional changes. The platform accommodates convenient completion without disrupting daily routines. High follow-up rates demonstrate continued user retention and perceived value of the system.

VII. DISCUSSION

A. Preventive Care and Early Detection

NeuroScan demonstrates the effectiveness of early detection and preventive mental health care using technology. The platform identifies emotional and behavioral reactions early, enabling intervention before disorders deteriorate to critical psychological states. This supports the principles of preventive healthcare, where timely insights are significant in enhancing long-term outcomes. Combining structured testing with facial emotion and behavioral indicators yields meaningful mental health information that aligns with clinically validated frameworks.

B. Role of Real-Time Systems

Timeliness is critical in mental health assessment and intervention. Delays in detecting emotional distress or behavioral change can diminish the effectiveness of support mechanisms. NeuroScan processes questionnaire responses, facial emotion data, and behavioral signals in near real-time during assessment, enabling rapid identification of emotional patterns and delivery of timely feedback.

C. User Engagement and Commitment

Sustained user engagement is required for effective mental health monitoring. NeuroScan integrates structured tests and interactive modules that enhance completion rates compared to passive systems. Real-time interactivity and feedback reduce assessment abandonment and improve data validity.

D. Limitations and Challenges

1) Scalability: Continuous facial analysis and assessment processing can create latency bottlenecks in high-frequency use environments. Centralized AI model deployment may face performance degradation as the user base grows, particularly during live interaction sessions.

2) Equity and Accessibility: The system's dependency on a camera-enabled device restricts access for some user groups. Effective use also requires basic digital literacy, which may exclude less tech-savvy populations.

E. Future Research Directions

Future work will focus on: (1) developing predictive machine learning models to estimate changes in individual mental health states using historical assessment data and behavioral trends; (2) enabling proactive identification of early warning signals to support preventive rather than reactive interventions; and (3) expanding multilingual and multi-cultural support for broader global accessibility.

VIII. CONCLUSION

NeuroScan demonstrates that current AI-based technology, including real-time data processing, facial emotion recognition, and intelligent assessment systems, can be successfully implemented for early mental health monitoring and preventive care. The platform's practical importance lies in combining systematic psychological testing with instant behavioral orientation to enhance the clarity and promptness of mental health analysis. The system architecture offers a scalable and flexible framework for continuous mental health evaluation, enabling timely detection of emotional distress and proactive intervention. Real-time user interaction, AI-driven facial emotion recognition, and individualized feedback collectively make mental health monitoring more accessible, reliable, and engaging for users.

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