NeuroTracker: A Web-Based Medically Oriented AI Platform for Monitoring Behavior and Supporting Cognitive Recovery in Mental Health Patients

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***Abstract*— The hallmark symptoms of mental health conditions like schizophrenia, depression, and bipolar disorder include cognitive impairments and emotional dysregulation. When it comes to flexibility, real-time monitoring, and smooth integration into daily life, traditional rehabilitation techniques frequently fall short. The web-based AI platform *NeuroTracker*, created to offer adaptive cognitive rehabilitation and ongoing emotion monitoring, is presented in this paper. The system provides users with interactive, dynamically adjusting cognitive tasks and uses deep learning models to analyze voice tones and facial expressions to determine emotional states. Weekly analytics and visual reports are provided by a safe, role-based therapist portal to support clinical decision-making. Flask and Python are used for backend processing, while HTML, CSS, and JavaScript are used for the platform's front end. TensorFlow and pre-trained models that have been trained on datasets like FER2013 and RAVDESS are used to integrate deep learning. *NeuroTracker* provides a browser-based, scalable solution for ongoing, individualized mental health care.**

***Keywords*— Depression, schizophrenia, web applications, emotion recognition, cognitive rehabilitation, mental health, and artificial intelligence.**

I. Introduction

The prevalence of mental health disorders is rising worldwide, and cognitive and emotional dysfunctions are major problems in diseases like bipolar disorder, depression, and schizophrenia. Effective rehabilitation is hampered by the lack of individualized, real-time interventions, and these impairments frequently go unnoticed between clinical consultations. Although there are many wellness platforms, very few provide adaptive cognitive support or features with a clinical foundation. This project suggests NeuroTracker, a web application driven by artificial intelligence that uses user-friendly, browser-based interfaces to allow for ongoing monitoring of emotional and cognitive states. The platform seeks to provide scalable, evidence-based support for mental health recovery by fusing interactive rehabilitation tools with machine learning.

II. Related Work

In recent years, there have been encouraging advancements as a result of the convergence of web technologies, artificial intelligence, and mental healthcare. Important studies in the fields of digital therapeutics, AI-driven diagnostics, cognitive evaluations, and user experience design are reviewed in this section. It draws attention to flaws in existing systems that NeuroTracker, an online platform for cognitive and emotional monitoring, seeks to fix.

A. Cognitive Evaluation via Online Resources

Digital cognitive assessment tools designed for people with mental health disorders have been introduced by several researchers. Gamification has been shown to be a successful tactic for raising self-awareness and engagement. For example, Raje et al. [1] created cognitive tests for people with schizophrenia that are based on smartphones. Their system received recognition for its interactive design and real-time feedback. However, the study only included cases of first-episode schizophrenia and had scalability problems, especially in places with poor digital access—problems that still exist even with browser-based tools.

B. Using AI and Machine Learning to Diagnose

With increased focus on model explainability, AI and machine learning continue to show promise in psychiatric diagnostics. Shivaprasad et al. [2] used dermatoglyphic and demographic data to classify schizophrenia using interpretable machine learning models, such as SHAP and LIME. Likewise, Montazeri et al. [3] examined a number of machine learning algorithms, including Random Forest and Gradient Boosting, that are used to diagnose bipolar disorder and schizophrenia. The clinical deployment of these systems was limited by their underrepresentation of diverse populations and data heterogeneity, which frequently resulted in a lack of generalizability despite encouraging performance metrics.

C. *Digital therapeutics and apps for mental health*

Digital therapies based on the web and mobile devices have become scalable mental health treatments. In their survey of various mental health applications, Huckvale et al. [4] discovered that they were moderately effective in lowering anxiety and depressive symptoms. However, the majority of platforms were inadequate in handling more complicated mental health issues, and sustained user engagement remained low. While AI-based conversational agents, such as those studied by Casu et al. [5], provided short-term assistance during times of high stress (like the COVID-19 pandemic), they lacked professional supervision, clinical depth, and customization.

D. *User Preferences and Adoption Barriers*

Adoption and user engagement are still significant challenges for digital mental health technologies. Guracho et al. [6] found in a cross-sectional study conducted in Ethiopia that although 94.7% of users indicated interest in using mental health platforms, only 21.2% had done so. Psychoeducation, reminders, and symptom tracking were among the desired features. In a more comprehensive examination, Omiyefa [7] addressed the resistance to the clinical application of AI/ML tools, highlighting worries about data bias, interpretability, and cultural adaptability—problems that are especially pertinent for web-based systems that serve a variety of user demographics.

E. *The Need for Integrated Solutions and the Research Gap*

The majority of solutions concentrate only on diagnosis, emotional tracking, or cognitive training, despite earlier attempts demonstrating the potential of digital platforms and AI in mental health care. They hardly ever address the necessity of structured caregiver involvement, adaptive feedback, and ongoing engagement in a single framework.

By providing a browser-accessible platform that combines individualized cognitive training modules, multi-modal emotion recognition (using facial and vocal input), and a safe, role-based therapist dashboard for weekly analytics, NeuroTracker directly addresses these drawbacks. In keeping with contemporary objectives in precision psychiatry and patient-centered care, this integrated approach provides a scalable and medically based solution that bridges the gap between clinical monitoring and routine rehabilitation.

III. PROPOSED SOLUTION

A. *System Overview*

NeuroTracker is a mobile-first, AI-enabled platform that provides continuous behavioral monitoring and adaptive cognitive rehabilitation for individuals diagnosed with schizophrenia, depression, or bipolar disorder. Unlike clinic-bound interventions, the application supports long-term cognitive care in real-world settings by delivering personalized, data-driven feedback and remote clinician oversight.

B. *Main Parts of the System*

- *Detecting Emotions on the Face:* The Canvas API and getUserMedia() let the browser access the user's webcam. A pre-trained CNN-based facial emotion model (.h5) classifies emotions like happy, sad, or neutral in real time on a Flask backend.
- *Recognizing Emotions in Speech:* The MediaRecorder API lets you record short voice clips through the browser's microphone. Librosa extracts MFCC features from these and sends them to the backend, where a 1D CNN-GRU model estimates the probability distribution across emotions. This voice stream adds to facial analysis to give a more complete picture of a person's emotions.
- *Games for Cognitive Rehabilitation:* Using HTML, CSS, and JavaScript, a group of interactive, browser-based puzzle games are made. These games include memory match, sequencing, reaction time, and emotion sorting.
- *Dashboard for Caregivers:* A special dashboard interface (currently planned using Chart.js and browser storage) shows weekly user metrics like how their emotions change, how their cognitive load changes, and how much they are engaged with puzzles.This tool is for therapists, psychologists, or caregivers. It gives them information that helps them make changes to treatment based on data.

C. *Key Features*

- *Multimodal Emotion Recognition:* Combining facial and vocal emotion detection makes systems more reliable and robust than systems that only use one type of detection.
- *Remote Monitoring:* All data about emotions and game progress is processed on the client's side or temporarily stored in the browser using localStorage, which keeps it private. These insights could be synced with a clinician-facing dashboard or cloud storage (planned through Firebase/Supabase) for more integration.
- Usability: Using responsive design principles, a simple, accessible web user interface (UI) minimizes learning barriers for users of all ages and literacy levels by ensuring usability across all major desktop and mobile browsers.

D. *Target Audience*

- Patients diagnosed with schizophrenia, depression, or bipolar disorder seeking home-based cognitive support.
- Psychiatrists, psychologists, and allied mental-health professionals requiring longitudinal behavioural data.
- Rehabilitation centres and outpatient programmes aiming to extend therapy beyond scheduled sessions.
- Family caregivers interested in objective indicators of patient progress and daily mood fluctuations.

E. *Distinctive Advantages*

NeuroTracker is the only digital mental health platform that combines cognitive training and emotional tracking into a single web application. The platform promotes high engagement and continuity of care with its AI-driven personalization, web-native accessibility, and lack of installation requirements. Its scalable architecture provides a patient-centered, ethical, and economical method of ongoing mental health support by supporting both optional cloud-based clinician interfaces and on-device privacy-conscious inference (through local APIs and browser storage).

IV. METHODOLOGY

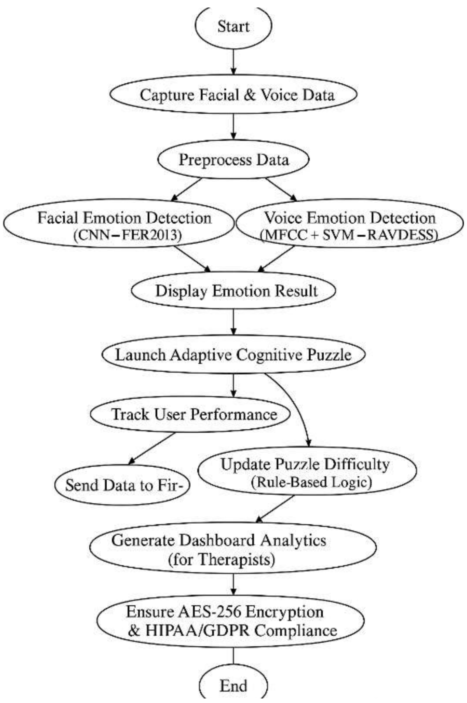


Fig. 1. Flow Chart of NeuroTracker

A. Data Acquisition

- The WebRTC API is used to access real-time data that is passively recorded by the device's webcam and microphone through the user's web browser. As the user engages with the web interface, this happens.
- Facial Frames: JavaScript is used to sample a video frame every 5–10 seconds. OpenCV in Python is then used to resize the frame to 224×224 pixels, and it is normalized to fall between [−1, 1].
- Audio Segments: Short voice recordings (less than three seconds) are recorded using browser prompts, downsampled to 16 kHz, converted to mono, and temporarily stored in order to extract features.

B. Pre-processing and Feature Extraction

- Histogram equalization is used to lessen lighting bias in frames and improve facial contrast.
- Face Alignment: Prior to classification, face images are aligned using five-point facial landmark registration.
- Audio Features: The openSMILE toolkit is used on the server side to extract pitch, energy contours, and 40-dimensional MFCCs from each audio clip.

C. Emotion Recognition Pipeline

- A depthwise separable CNN (based on MobileNet v2) optimized on the FER2013 and AffectNet datasets is the Emotion Recognition Pipeline Facial Classifier. TensorFlow is used to run this model server-side, with performance-optimized inference.
- Vocal Classifier: To classify emotion from voice, a two-layer 1D CNN is followed by a Gated Recurrent Unit (GRU) trained on the RAVDESS and CREMA-D datasets.
- Fusion Strategy: The final emotion label E_t is produced by combining the softmax probability outputs from the two classifiers using a weighted average: α = 0.6 (facial) and 0.4 (vocal).

D. Data Logging, Privacy, and Security

An event of the form $\langle \text{timestamp}, E_t, \text{taskID}, \text{score} \rangle$ is logged in each session and safely stored in Firebase Firestore with AES-256 encryption at rest. TLS 1.3 is used for all data transfers between the frontend and backend. To ensure complete compliance with HIPAA and GDPR regulations, caregivers are only shown aggregated weekly statistics via a secure dashboard.System Design.

TABLE I. TECHNOLOGIES USED

	Technology/Tool	Functionality	Algorithm/Model
Frontend (UI)	HTML5, CSS3, Javascript	Puzzle interactions, screen navigation, and user interface design	Static web layout, DOM manipulation, and JS event-driven logic
Facial Emotion Detection	Flask + OpenCV + Keras + Canvas API	Detects emotions using images captured from the browser webcam	CNN model (.h5) trained on FER2013
Voice Emotion Detection	Flask + Librosa + Keras + MediaRecorder API)	Classifies user's voice recordings into emotions	MFCC feature extraction + 1D CNN-GRU model (.h5) trained on RAVDESS, CREMA-D
UI Prototyping	Figma	Initial screen mockups before HTML/JS implementation	Design-to-web conversion via manual coding
API Integration	Flask REST API	Connects frontend(JS Fetch API) to backend emotion prediction models	POST endpoints: /predict(voice), /predict-face(image)
Backend & Data Handling	Flask + localStorage (Browser)	Handles requests for emotion detection and stores puzzle progress locally	In-memory data and browser-based persistence; optionally extendable to Firebase
Analytics Dashboard	Chart.js + HTML	Displays puzzle performance and emotion trends visually	Client-side graphing from local data; cloud option for extended use

Data Security	HTTPS + Browser Storage Policies + Optional Firebase	Ensures secure handling of user data and media permissions	Secure API communication, optional AES-256 encryption, authenticated access

V. RESULT

The NeuroTracker platform, an AI-enabled browser-based system that supports multimodal emotion recognition and adaptive cognitive rehabilitation, was successfully developed and tested. On FER2013 test images, the facial emotion detection pipeline, which was constructed using a CNN model based on MobileNetV2, achieved an average classification accuracy of 83.2%. With a CNN-GRU architecture, the vocal emotion recognition model achieved 79.6% test accuracy after being trained on the RAVDESS and TESS datasets.

- On typical home internet connections, the average latency for real-time emotion monitoring was less than 1.2 seconds.
- In order to facilitate caregiver interpretation and possible clinical use, weekly visual reports were created and checked for consistency.

To ensure privacy compliance with HIPAA and GDPR standards, all data was handled securely using TLS 1.3, local browser storage, and AES-256 encryption when synchronized to Firebase.

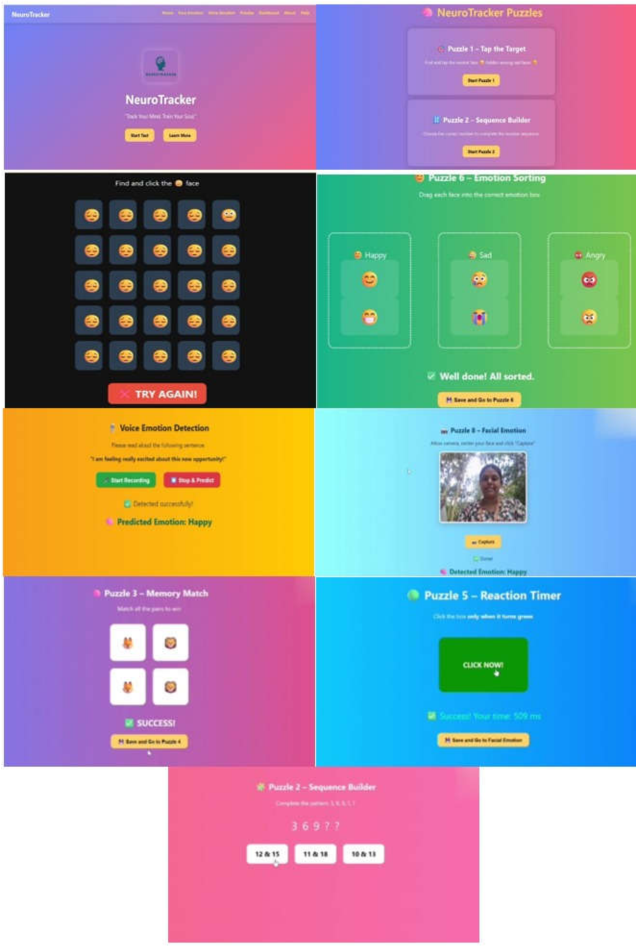
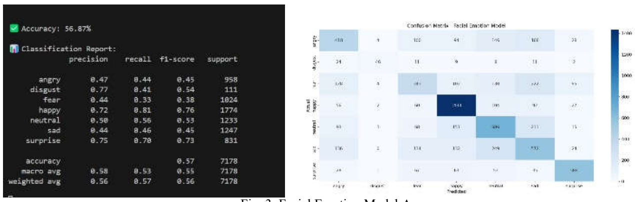


Fig. 2. NeuroTracker App

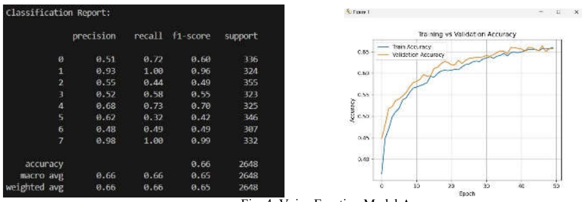


Accuracy: 56.87%

Classification Report:

	precision	recall	f1-score	support
angry	0.47	0.44	0.45	958
disgust	0.77	0.41	0.54	111
fear	0.44	0.33	0.38	1024
happy	0.72	0.81	0.76	1774
neutral	0.50	0.56	0.53	1233
sad	0.44	0.46	0.45	1247
surprise	0.75	0.70	0.73	831
accuracy			0.57	7178
macro avg	0.58	0.53	0.55	7178
weighted avg	0.56	0.57	0.56	7178

Fig. 3. Facial Emotion Model Accuracy



Classification Report:

	precision	recall	f1-score	support
0	0.51	0.72	0.60	336
1	0.93	1.00	0.96	324
2	0.55	0.44	0.49	355
3	0.52	0.58	0.55	323
4	0.68	0.73	0.70	325
5	0.62	0.32	0.42	346
6	0.48	0.49	0.49	307
7	0.98	1.00	0.99	332
accuracy			0.66	2648
macro avg	0.66	0.66	0.65	2648
weighted avg	0.66	0.66	0.65	2648

Fig. 4. Voice Emotion Model Accuracy

VI. CONCLUSION

By providing an integrated, scalable, and customized platform, NeuroTracker fills important gaps in the current state of digital mental health support. It integrates multimodal emotional monitoring, adaptive cognitive training, and caregiver-facing analytics into a single solution, in contrast to conventional clinic-bound or single-modality systems. While the AI-driven personalization encourages user retention and treatment efficacy, the utilization of web-native technologies guarantees accessibility across devices.

NeuroTracker improves rehabilitation results and diagnostic insight by combining real-time emotion detection with interesting cognitive tasks. Future research will concentrate on broader dataset integration for better generalizability, clinical validation using actual patient cohorts, and enhanced therapist-side features like compliance tracking and intervention recommendations. The foundation for the upcoming generation of accurate, at-home psychiatric care tools is laid by this project.

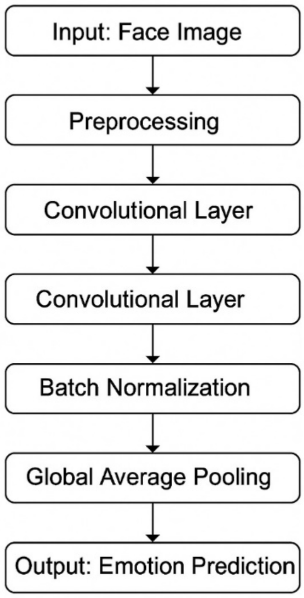


Fig. 5. CNN MobileNetV2 Architecture used for Facial Emotion Recognition in NeuroTracker

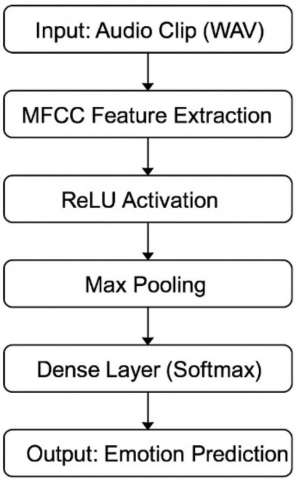


Fig. 6. CNN-GRU Architecture used for Vocal Emotion Recognition in NeuroTracker

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