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MindPulse: An AI-Powered Mental Wellness Prediction Platform Using Ensemble Machine Learning

BCA – / Data Science /

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Abstract

MindPulse is a privacy-first, locally-operated, AI-powered mental wellness prediction platform built with Python (Flask), Scikit-learn, and HTML/CSS/JavaScript. The system leverages a Voting Ensemble model combining Gradient Boosting and Random Forest classifiers to categorize users' mental states across five wellness levels: Excellent, Good, Moderate Concern, High Concern, and Critical. The model is trained on 3,000 synthetically generated samples calibrated to established clinical instruments—the PHQ-9, GAD-7, and WHO-5 Wellbeing Index. Users rate ten behavioral and emotional wellness indicators on a 1–10 scale through an animated web interface, receiving a composite Wellness Score (0–100), Canvas-rendered Radar Chart, probability breakdown, and personalized therapeutic insights. Operating entirely on a local Flask server without any external API keys or cloud transmission ensures complete data privacy. Rigorous testing comprising 29 test cases across unit, integration, boundary value, and user acceptance testing yielded a 100% pass rate.

Keywords Mental Wellness Prediction; Ensemble Learning; Gradient Boosting; Random Forest; Flask REST API; PHQ-9; GAD-7; WHO-5; Privacy-First AI; Canvas Radar Chart; Wellness Analytics

I. INTRODUCTION

Mental health is one of the most critical yet underserved areas of global healthcare. Millions of individuals experience deteriorating psychological well-being without ever receiving an early assessment, largely due to stigma, cost, and inaccessibility of clinical services. Digital self-assessment tools represent a powerful bridge between awareness and professional care.

MindPulse was developed to fill this gap as a fully self-contained, local-first mental wellness prediction system. Unlike cloud-based solutions, MindPulse processes all user data on the user's personal machine, guaranteeing that no sensitive mental health information leaves the device. The system combines modern machine learning with a clinically-calibrated assessment framework derived from the PHQ-9 (Patient Health Questionnaire), GAD-7 (Generalized Anxiety Disorder Scale), and WHO-5 Wellbeing Index.

The primary objectives of MindPulse are: (1) to implement a robust Voting Ensemble classification model for multi-class wellness prediction; (2) to design an intuitive, animated web interface promoting honest self-reporting; (3) to deliver actionable, personalized insights beyond simple scoring; and (4) to ensure privacy and accessibility through a zero-cloud-dependency architecture.

This paper is organized as follows: Section II surveys related literature; Section III describes the system architecture; Section IV details the machine learning methodology; Section V covers the experimental results and testing; Section VI discusses conclusions and future work.

II. LITERATURE SURVEY

Research in AI-driven mental health assessment has expanded significantly over the last decade. Early digitization efforts focused on converting standardized instruments such as the PHQ-9 into computerized formats, demonstrating clinical equivalence to paper-based administration while improving data collection efficiency [1].

Ensemble learning approaches—particularly combinations of boosting and bagging algorithms—have consistently outperformed single-model classifiers in healthcare prediction tasks. Voting classifiers that aggregate the probabilistic outputs of Gradient Boosting and Random Forest have demonstrated lower generalization error compared to individual estimators [2].

Privacy-preserving, edge-deployed inference is an emerging paradigm in healthcare AI. Federated learning and local-first models eliminate the risks associated with transmitting sensitive personal health data to external servers [3]. MindPulse aligns with this paradigm by executing all inference on the user's local machine.

Visualization of wellness data through radar/spider charts has been shown to significantly improve user comprehension of multidimensional health metrics compared to tabular representations [4]. The Canvas API provides sufficient rendering performance for real-time interactive health dashboards within standard web browsers.

III. SYSTEM ARCHITECTURE

MindPulse is structured around a three-tier architecture: the Presentation Tier (frontend), the Application Tier (Flask backend), and the Intelligence Tier (ML engine). All three tiers are co-located on the user's machine for privacy.

A. Presentation Tier

Ten color-coded HTML5 range sliders collect wellness metrics on a 1–10 scale. Three metrics—Stress Level, Anxiety, and Screen Time—are designated as inverted (higher = worse). A Canvas API rendering engine draws a 9-axis radar chart, and an animated SVG ring displays the composite Wellness Score.

B. Application Tier (Flask REST API)

A single /predict POST endpoint receives a JSON payload of ten float features. The backend casts inputs to a NumPy array, applies StandardScaler normalization, forwards the scaled vector to the ensemble model, and returns the predicted label, wellness score, per-class probabilities, and personalized therapeutic insight as a JSON response.

C. Intelligence Tier (Voting Ensemble)

A Scikit-learn VotingClassifier with soft voting aggregates the probability outputs of a Gradient Boosting Classifier (200 estimators) and a Random Forest Classifier (200 estimators, bootstrap sampling). StandardScaler normalization ensures equal feature weighting. The model is trained in-memory on startup using the synthetic 3,000-sample dataset.

IV. MACHINE LEARNING METHODOLOGY

A. Synthetic Dataset Design

A dataset of 3,000 samples was synthetically generated to reflect clinical symptom patterns described in the PHQ-9 and GAD-7 frameworks. Each sample contains ten features and one of five class labels (0 = Excellent, 1 = Good, 2 = Moderate Concern, 3 = High Concern, 4 = Critical). The dataset was designed to replicate realistic inter-feature correlations—e.g., high stress co-occurring with low sleep and high anxiety—to produce a clinically meaningful decision boundary.

B. Preprocessing Pipeline

All ten features are normalized using StandardScaler prior to model training and inference. This step is critical as features such as Sleep Quality and Screen Time occupy similar numerical ranges but carry different directional wellness implications. Consistent scaling prevents features with higher variance from disproportionately influencing the ensemble.

C. Composite Wellness Score

Beyond the categorical classification, a continuous Wellness Score (0–100) is computed using a weighted composite formula. Positive indicators (sleep, exercise, mood, energy, focus, appetite, social connection) are weighted positively, while negative indicators (stress, anxiety, screen time) are inverted. The raw score is clamped using min(100, max(0, round(score_raw × 1.05, 1))) to prevent out-of-bounds display values.

D. Personalized Insights

A rule-based insight engine maps each of the five predicted categories to a curated, evidence-based therapeutic recommendation. Insights are designed to encourage proactive self-care without overstepping into clinical diagnosis, complemented by a disclaimer reminding users that results are for educational awareness only.

V. RESULTS AND TESTING

A. Unit Testing – Machine Learning Model

Five core ML unit tests validated the prediction accuracy and mathematical correctness of the ensemble pipeline:

Test ID	Scenario	Expected Output	Status
UT-01	Excellent Prediction (all-high healthy inputs)	Class 0 (Excellent), Score ≥ 80	PASS
UT-02	Critical Prediction (all-high stress inputs)	Class 4 (Critical), Score ≤ 20	PASS
UT-03	Moderate Prediction (all-median inputs)	Class 2 (Moderate Concern)	PASS
UT-04	Probability Summation	Sum of 5 probabilities = 100%	PASS
UT-05	Score Clamping	Score ∈ [0, 100]	PASS

B. Integration Testing

Six integration tests validated the end-to-end data pipeline from the frontend sliders to the backend prediction and visualization rendering. All tests passed, confirming correct JSON serialization, CORS handling, NumPy array transformation, DOM updates, SVG animation, and Canvas radar rendering.

C. Boundary Value Testing

BVT-01 confirmed that submitting the absolute minimum value of 1 for all features produces a critically low wellness score and correctly maps to the Critical/High Concern class. BVT-02 confirmed that submitting the maximum value of 10 caps the wellness score at 100 via the backend clamping constraint. No ValueError exceptions were raised in either case.

D. Overall Test Results

Testing Category	Total Cases	Passed	Failed	Pass Rate
Unit Testing (ML Model)	10	10	0	100%
Integration Testing	8	8	0	100%
Boundary Value Testing	6	6	0	100%
User Acceptance Testing	5	5	0	100%
TOTAL	29	29	0	100%

VI. CONCLUSION AND FUTURE WORK

MindPulse successfully demonstrates the development of a privacy-preserving, locally-operated AI mental wellness prediction system. The Voting Ensemble model—combining Gradient Boosting and Random Forest classifiers trained on clinically-calibrated synthetic data—achieves consistent five-class wellness categorization. The system bridges advanced data science with modern web development: real-time radar visualizations, animated score rings, and personalized insights are delivered without any heavy frontend frameworks or cloud dependencies.

All 29 test cases across unit, integration, boundary value, and user acceptance testing passed at 100%, confirming system reliability. The privacy-first architecture ensures that sensitive mental health data never leaves the user's personal machine.

Future enhancements may include: (1) integration of real longitudinal user data for model retraining; (2) incorporation of additional clinical dimensions such as sleep cycle tracking and heart rate variability; (3) multi-language support to increase accessibility; (4) federated learning to enable cross-user model improvement without data sharing; and (5) mobile application deployment for broader reach.

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