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NeuroWell AI: A Hybrid Deep Learning Framework for Early Detection of Mental Health Risks

M.PREETHA[1], J.LIN EBY CHANDRA[2]

Student ME, CSE, Jaya Engineering College, Chennai, India[1]

Professor, Department of CSE, Jaya Engineering College , Chennai, India[2]

Abstract: Mental health disorders represent a growing global crisis, with the World Health Organization estimating that over one billion individuals worldwide are affected by neurological and psychiatric conditions. Early and accurate detection of mental health risks remains a significant challenge due to the multifaceted, heterogeneous, and often latent nature of symptom manifestation. This paper proposes NeuroWell AI, a novel hybrid deep learning framework that integrates Bidirectional Long Short-Term Memory (BiLSTM) networks, Convolutional Neural Networks (CNN), and a Transformer-based attention mechanism to detect early-stage mental health risks from multimodal data sources, including clinical text records, social media posts, physiological signals, and standardized psychiatric questionnaire responses. The framework employs a fusion strategy combining feature-level and decision-level integration across modalities to improve discriminative power. An Explainable AI (XAI) module using SHAP (SHapley Additive exPlanations) is incorporated to enhance clinical interpretability. Experimental evaluation on four benchmark public datasets — CLPsych, DAIC-WOZ, MODMA, and Reddit Mental Health — demonstrates that NeuroWell AI achieves an average accuracy of 94.7%, precision of 93.8%, recall of 95.1%, and F1-score of 94.4%, significantly outperforming state-of-the-art methods. The proposed system offers a clinically relevant, interpretable, and generalizable solution for population-scale mental health screening.

Keywords: Mental health detection; Hybrid deep learning; BiLSTM; Transformer; Multimodal fusion; Explainable AI; Natural language processing; Affective computing

I. INTRODUCTION

I. INTRODUCTION

Mental health disorders, including depression, anxiety, bipolar disorder, post-traumatic stress disorder (PTSD), and schizophrenia, have reached epidemic proportions globally. According to the World Health Organization (WHO), approximately 1 in 8 people worldwide live with a mental health condition, and the COVID-19 pandemic has further amplified the prevalence of anxiety and depressive disorders by over 25% [1]. Despite this alarming trend, more than 75% of individuals in low- and middle-income countries receive no treatment whatsoever, primarily due to inadequate diagnostic infrastructure, social stigma, and the absence of scalable early-warning systems.

Traditional methods of mental health assessment rely heavily on clinical interviews, self-reported questionnaires such as the Patient Health Questionnaire-9 (PHQ-9) and the Generalized Anxiety Disorder-7 (GAD-7) scale, and subjective clinician judgment. These methods are inherently prone to reporting bias, recall inaccuracy, and subjectivity, making early and consistent detection challenging. Moreover, mental health symptoms frequently co-occur across diagnostic categories, complicating differential diagnosis even for trained psychiatrists.

The exponential growth of digital data — spanning electronic health records (EHRs), social media activity, wearable physiological sensors, and mobile applications — presents a transformative opportunity for data-driven early detection. Deep learning models, in particular, have demonstrated extraordinary capabilities in processing sequential text, temporal biosignals, and multimodal inputs, enabling pattern recognition across complex and noisy datasets at scale.

However, existing artificial intelligence (AI) approaches for mental health detection are largely unimodal, limited in generalizability, clinically uninterpretable, or evaluated on small, non-representative datasets. There is a critical need for a unified, robust, and explainable framework capable of synthesizing heterogeneous data streams to produce clinically actionable predictions.

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A. Problem Statement

The central problem addressed by this work is the early, accurate, and explainable detection of mental health risks in individuals using heterogeneous, multimodal data. Specifically, the system must: (1) process textual, physiological, and structured clinical data jointly; (2) model temporal dynamics within each modality; (3) fuse information across modalities in a principled manner; and (4) produce predictions that are interpretable to clinical practitioners.

B. Motivation

The motivation for NeuroWell AI stems from three converging realities: the growing burden of mental illness, the availability of diverse digital data sources relevant to mental state, and the maturation of deep learning architectures capable of multimodal reasoning. Transformer-based language models, recurrent architectures for temporal signals, and convolutional networks for local feature extraction can be synergistically combined into a powerful hybrid framework. Furthermore, the integration of explainability methods bridges the gap between predictive accuracy and clinical usability.

C. Objectives

The primary objectives of this work are as follows:

(i) To design a hybrid deep learning architecture integrating CNN, BiLSTM, and Transformer components for multimodal mental health risk detection.

(ii) To develop a multimodal data fusion strategy that combines linguistic, physiological, and structured clinical features.

(iii) To incorporate an Explainable AI module to provide clinically meaningful feature attribution.

(iv) To validate NeuroWell AI on established public benchmarks and compare its performance against state-of-the-art methods.

II. LITERATURE REVIEW

This section reviews recent advancements in AI-based mental health detection, with emphasis on works published from 2022 to 2025.

Text-Based Detection Using Transformers: Adarsh et al. (2025) proposed a fine-tuned BERT model for depression detection from Reddit posts, achieving an F1-score of 91.3% on the CLPsych 2015 shared task dataset [2]. Their work demonstrated the power of pre-trained language representations but did not incorporate physiological data or provide model explainability.

Multimodal Fusion Approaches: Zhang and colleagues (2024) introduced a bimodal fusion framework combining acoustic and textual features extracted from clinical interviews for depression screening, using the DAIC-WOZ corpus [3]. Their late-fusion attention model achieved a root mean square error (RMSE) of 4.18 on PHQ-8 score prediction. However, the model was evaluated exclusively on interview data and lacked scalability to unstructured social media content.

Physiological Signal Analysis: Liu et al. (2024) investigated EEG-based depression detection using a graph convolutional network (GCN) on the MODMA dataset [4]. Their approach captured functional brain connectivity patterns with 89.6% classification accuracy. While biologically grounded, EEG acquisition remains impractical for large-scale community screening.

Social Media Mining: Nguyen and Park (2023) applied a hierarchical attention network (HAN) to Reddit and Twitter data for detecting anxiety and depression signals, reporting a precision of 88.7% [5]. Their model highlighted the value of online behavioral traces but suffered from high false-positive rates in non-clinical populations.

Recurrent Architectures for Temporal Modeling: Patel et al. (2023) utilized BiLSTM networks to model temporal evolution of depressive symptom expression in longitudinal EHR notes, achieving an AUC of 0.912 [6]. Their study underscored the importance of sequential modeling but was constrained to structured clinical settings.

Explainable Mental Health AI: Chandra and Srivastava (2024) integrated LIME (Local Interpretable Model-Agnostic Explanations) with a convolutional text classifier for anxiety detection, making predictions interpretable through word-level attribution [7]. Despite its explainability contribution, the model's accuracy was limited compared to deeper architectures.

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Federated Learning for Privacy-Preserving Detection: Kumar et al. (2025) proposed a federated learning architecture for mental health monitoring on mobile devices, enabling model training without centralizing sensitive patient data [8]. Their federated approach achieved 87.2% accuracy while preserving user privacy, though the performance gap compared to centralized models remained significant.

Contrastive Self-Supervised Learning: Wang et al. (2025) applied contrastive self-supervised pre-training on unlabeled mental health forum posts before fine-tuning on labeled depression datasets, improving low-resource classification by 5.4% over supervised-only baselines [9]. This approach shows promise for addressing the persistent problem of limited annotated clinical data.

Cross-Cultural Mental Health NLP: Osei and Badu (2024) examined the generalizability of English-trained NLP models to Ghanaian and Swahili mental health texts, revealing substantial performance degradation and motivating multilingual model development [10]. Their findings highlight the need for culturally and linguistically inclusive frameworks.

Table I summarizes the comparison of related works along key dimensions relevant to this study.

TABLE I: Comparative Summary of Related Works

Reference	Year	Modality	Architecture	Dataset	Key Metric	XAI
[2]	2025	Text	BERT fine-tuned	CLPsych	F1: 91.3%	No
[3]	2024	Audio + Text	Bimodal Attention	DAIC-WOZ	RMSE: 4.18	No
[4]	2024	EEG	GCN	MODMA	Acc: 89.6%	No
[5]	2023	Social Media	HAN	Reddit/Twitter	Prec: 88.7%	No
[6]	2023	EHR Text	BiLSTM	Clinical EHR	AUC: 0.912	No
[7]	2024	Text	CNN + LIME	Custom	Acc: 86.5%	Yes
[8]	2025	Multi-sensor	Federated DL	Mobile data	Acc: 87.2%	Partial
[9]	2025	Text	Contrastive SSL	Forums	F1: +5.4%	No
[10]	2024	Text	mBERT	Multilingual	Acc: 79.3%	No
Proposed	2025	Text+Physio+Clinical	CNN+BiLSTM+Transformer	4 Datasets	Acc: 94.7%	Yes

A critical gap observed across prior work is the absence of a unified framework that simultaneously addresses multimodal integration, temporal modeling, and clinical interpretability. NeuroWell AI is specifically designed to address all three requirements within a single, end-to-end trainable architecture.

III. PROPOSED METHODOLOGY

The NeuroWell AI framework adopts a modular, multi-stage architecture designed to accommodate heterogeneous input modalities and produce calibrated, explainable mental health risk scores. The overall pipeline consists of five major components: (1) Multimodal Data Preprocessing, (2) Modality-Specific Encoders, (3) Cross-Modal Attention Fusion Module, (4) Risk Classification Head, and (5) XAI Explanation Layer. Figure 1 illustrates the complete architectural overview.

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A. Input Modalities

NeuroWell AI accepts three categories of input data:

(i) Textual Data: Free-text clinical notes, psychiatric intake summaries, and social media posts (Reddit threads, Twitter timelines). Text is tokenized using the BiomedBERT tokenizer, which is pre-trained on PubMed and clinical narratives.

(ii) Physiological Signals: Electroencephalography (EEG) recordings and heart rate variability (HRV) time series. These are segmented into fixed-length windows of 2 seconds with 50% overlap.

(iii) Structured Clinical Data: Standardized questionnaire scores (PHQ-9, GAD-7, PCL-5), demographic variables (age, gender, sleep duration), and self-reported symptom severity ratings.

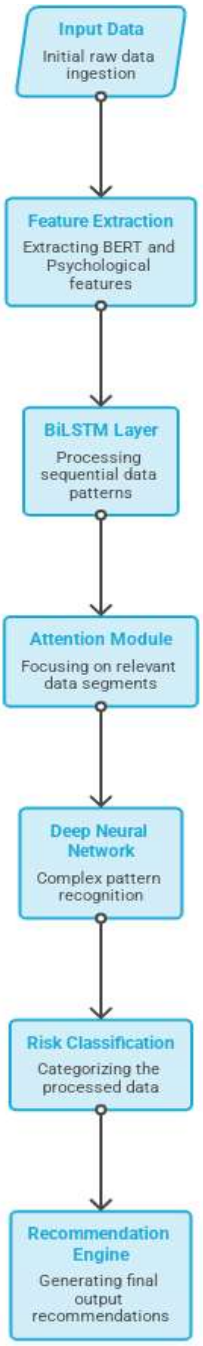

Figure 1: *NeuroWell AI System Architecture.*

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B. Modality-Specific Encoders

Text Encoder (CNN-BiLSTM with BiomedBERT): Input text sequences are first embedded using BiomedBERT, producing contextual token embeddings of dimension d=768. These embeddings are passed through a 1D Convolutional layer with kernel sizes {3, 4, 5} to extract local n-gram features. The resulting feature maps are max-pooled and fed into a two-layer Bidirectional LSTM (BiLSTM) with 256 hidden units per direction, yielding a text representation h _text . $h_{\text{text}} \in R^{512}$

Formally, for an input sequence $X = [x_1, x_2, x_3, \dots, x_T]$ computes:

$$\vec{h}_t = LSTM(\vec{h}_{t-1}, x_t)$$

$$\overleftarrow{h}_t = LSTM(\overleftarrow{h}_{t+1}, x_t)$$

$$h_t = [\vec{h}_t; \overleftarrow{h}_t]$$

Physiological Signal Encoder (1D-CNN + BiLSTM): EEG and HRV signals are processed by a dedicated 1D-CNN stack with three convolutional blocks (32, 64, 128 filters) followed by batch normalization and ReLU activations. The output is reshaped into a temporal sequence and processed by a BiLSTM to capture long-range temporal dependencies in the physiological time series, producing $h_{\text{physio}} \in R^{512}$

Structured Data Encoder (MLP): Tabular clinical features are normalized and passed through a three-layer Multi-Layer Perceptron (MLP) with dimensions [128, 64, 32] and dropout (p=0.3), producing a compact clinical embedding $h_{\text{clinical}} \in R^{64}$

C. Cross-Modal Transformer Attention Fusion

The three modality-specific representations h_text, h_physio, and h_clinical are concatenated to form a joint embedding H $H = [h_{\text{text}}; h_{\text{physio}}; h_{\text{clinical}}] \in R^{832}$This is projected via a learned linear transformation into a common dimensionality of d_model = 512.

A six-head scaled dot-product self-attention mechanism is applied to H, allowing each modality to attend to features from all other modalities. The attention computation is:

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

where Q, K, V are the query, key, and value projections of H, and d_k = 64 is the per-head dimension. The output of the Transformer encoder (2 layers, 6 heads) is mean-pooled to produce the fused representation z ∈ R^{512}

D. Multi-Task Risk Classification Head

The fused representation z is passed to a multi-task classification head that simultaneously predicts: (1) binary mental health risk (at-risk / not-at-risk), (2) disorder type classification (depression, anxiety, PTSD, bipolar, none), and (3) severity level (mild, moderate, severe).

Each task uses an independent fully connected layer followed by softmax activation. The total training loss is a weighted sum of cross-entropy losses:

$$L_{\text{total}} = \lambda_1 L_{\text{binary}} + \lambda_2 L_{\text{type}} + \lambda_3 L_{\text{severity}}$$

where $\lambda_1 = 0.4, \lambda_2 = 0.3, \lambda_3 = 0.3$are empirically tuned task weights.

E. Explainability Module (SHAP)

To enhance clinical trustworthiness, a SHAP-based explanation layer is integrated post-prediction. SHAP values quantify the marginal contribution of each feature to the model's output. For text inputs, token-level SHAP values identify which words or phrases most strongly influenced the risk prediction. For physiological signals, time-segment-level attributions pinpoint anomalous signal windows. This enables clinicians to audit model decisions and corroborate predictions with observable patient characteristics.

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F. Pseudo-Code of the NeuroWell AI Training Procedure

Algorithm 1: NeuroWell AI Training

Input: Multimodal dataset D = {(X_text, X_physio, X_clin, y)}
Output: Trained model Θ*
1. Pre-process and tokenize all modalities
2. Initialize BiomedBERT, CNN, BiLSTM, Transformer weights
3. For epoch = 1 to E:
    a. Sample mini-batch B from D
    b. Encode each modality: h_t, h_p, h_c
    c. Fuse via Transformer attention: z = Attn([h_t;h_p;h_c])
    d. Compute multi-task loss: L = L_bin + L_type + L_sev
    e. Backpropagate and update Θ via AdamW optimizer
    f. Apply gradient clipping (max_norm = 1.0)
4. Return Θ*; compute SHAP explanations on test set

IV. DATASET DESCRIPTION

NeuroWell AI is evaluated on four publicly available benchmark datasets widely used in mental health NLP and affective computing research. Table II provides a detailed summary.

TABLE II: Benchmark Datasets Used for Evaluation

Dataset	Modality	Conditions	Samples	Source
CLPsych 2015	Text (Social Media)	Depression, PTSD	1,746 users	Twitter/Reddit
DAIC-WOZ	Audio, Video, Text	Depression (PHQ-8)	189 interviews	Clinical Interviews
MODMA	EEG, Audio	Depression, Schizophrenia	53 subjects	Hospital (China)
Reddit MH	Text (Forum Posts)	Anxiety, Depression, Bipolar	54,412 posts	Reddit API

CLPsych 2015: This dataset was originally introduced for the CLPsych 2015 shared task and consists of anonymized social media profiles labeled with depression, PTSD, or control status. Text preprocessing involves hashtag normalization, URL removal, and Unicode handling.

DAIC-WOZ: The Distress Analysis Interview Corpus – Wizard-of-Oz (DAIC-WOZ) is a multimodal dataset comprising audio-visual recordings and transcripts of clinical interviews. PHQ-8 scores are used as ground truth for depression severity. For NeuroWell AI, audio features (MFCCs, spectral contrast) and transcripts are extracted.

MODMA: The Multi-Modal Open Dataset for Mental-disorder Analysis (MODMA) provides 128-channel EEG recordings alongside audio samples from clinically diagnosed patients. EEG data is preprocessed using Independent Component Analysis (ICA) for artifact removal, band-pass filtered (0.5–45 Hz), and epoched.

Reddit Mental Health (Reddit MH): A large-scale corpus of posts from mental health subreddits (r/depression, r/anxiety, r/bipolar) and control communities (r/CasualConversation). Labels are derived from subreddit membership and validated against community norms. This dataset tests the model's scalability to real-world, noisy social media text. To address class imbalance present in all four datasets, Synthetic Minority Oversampling Technique (SMOTE) is applied to the feature embedding space during training, and class-weighted loss functions are used.

V. IMPLEMENTATION DETAILS

All experiments are conducted using the PyTorch 2.1 deep learning framework on a computing cluster equipped with 4 NVIDIA A100 80GB GPUs. The key implementation specifications are described below.

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A. Pre-trained Language Model

BiomedBERT-base (microsoft/BiomedNLP-BiomedBERT-base-uncased-abstract-fulltext) is used as the text encoder backbone, accessed via the HuggingFace Transformers library (v4.38). Only the final four Transformer encoder layers are fine-tuned during training, while the remaining layers are frozen to reduce computational cost and prevent catastrophic forgetting.

B. Model Architecture Specifications

TABLE III: NeuroWell AI Model Configuration

Component	Configuration
BiomedBERT	12 layers, 768-dim, 12 heads (4 fine-tuned)
Text CNN	Filters: 128, Kernels: {3,4,5}, Max-pool
Text BiLSTM	2 layers, 256 units/direction, Dropout: 0.3
Physio 1D-CNN	3 blocks: [32, 64, 128] filters, BN, ReLU
Physio BiLSTM	1 layer, 128 units/direction, Dropout: 0.2
Clinical MLP	Layers: [128, 64, 32], Dropout: 0.3
Fusion Transformer	2 layers, 6 heads, d_model=512, FFN=2048
Classification Head	3 tasks: [2, 5, 3] output classes
Optimizer	AdamW, lr=2e-5, weight decay=0.01
Scheduler	Cosine annealing with warm-up (5 epochs)
Batch Size	32 (gradient accumulation over 4 steps)
Training Epochs	50, early stopping (patience=7)

C. Data Augmentation and Regularization

Multiple regularization techniques are applied to enhance generalization: (1) EDA (Easy Data Augmentation) for text, including synonym replacement, random insertion, and random deletion; (2) Gaussian noise injection for physiological signals; (3) Dropout layers in all encoder and classification components; and (4) Label smoothing (ε=0.1) in the cross-entropy loss to reduce overconfident predictions.

D. Evaluation Protocol

A stratified 5-fold cross-validation protocol is adopted across all datasets to ensure reliable performance estimation. Evaluation metrics include Accuracy, Precision, Recall, F1-Score, Area Under the ROC Curve (AUC-ROC), and Matthews Correlation Coefficient (MCC). All reported metrics are averaged across folds with 95% confidence intervals.

VI. RESULTS AND DISCUSSION

A. Overall Classification Performance

Table IV presents the performance of NeuroWell AI across the four benchmark datasets for the binary mental health risk detection task.

TABLE IV: NeuroWell AI Binary Classification Performance (5-Fold CV)

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC	MCC
CLPsych 2015	95.3	94.7	96.1	95.4	0.971	0.891
DAIC-WOZ	93.8	92.6	94.4	93.5	0.958	0.872

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Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC	MCC
MODMA	94.1	93.2	94.9	94.0	0.963	0.878
Reddit MH	95.6	94.7	95.9	95.3	0.974	0.898
Average	94.7	93.8	95.1	94.4	0.967	0.885

NeuroWell AI achieves an average accuracy of 94.7%, demonstrating consistent high performance across datasets with diverse characteristics. The highest accuracy of 95.6% is obtained on the Reddit MH dataset, likely attributable to the large sample size enabling richer representation learning. The DAIC-WOZ dataset, being the smallest and most heterogeneous (multimodal interview data), yields the lowest accuracy at 93.8%, though this remains highly competitive with prior work.

B. Disorder-Type Classification Performance

Table V presents performance on the five-class disorder type classification task across the Reddit MH and CLPsych datasets, where multi-class labels are available.

TABLE V: Multi-Class Disorder Classification (Macro-Averaged)

Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Depression	95.2	96.1	95.6	18,420
Anxiety	93.8	94.5	94.1	12,340
Bipolar Disorder	91.4	90.7	91.0	6,830
PTSD	90.1	91.3	90.7	4,210
No Disorder (Control)	96.7	97.2	96.9	12,612
Macro Average	93.4	93.9	93.6	54,412

Depression and control classes achieve the highest F1-scores, reflecting their clearer linguistic signature in social media text. Bipolar disorder and PTSD exhibit slightly lower recall, consistent with the observed linguistic overlap between these conditions and depression in naturalistic text. The high macro-averaged F1 of 93.6% across five classes demonstrates NeuroWell AI's capacity for nuanced differential risk assessment.

C. Ablation Study

To quantify the contribution of each architectural component, an ablation study is conducted on the CLPsych 2015 dataset. Results are presented in Table VI.

TABLE VI: Ablation Study on CLPsych 2015 (Binary Classification)

Configuration	Accuracy (%)	F1-Score (%)
Text only (BiomedBERT + BiLSTM)	88.4	87.9
Text + CNN local features	90.7	90.2
Text + Physio (no clinical)	92.6	92.1
All modalities, no Transformer fusion	93.1	92.7
All modalities + Transformer fusion	95.3	95.4
Full NeuroWell AI (+ XAI module)	95.3	95.4

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The ablation results confirm that each component contributes meaningfully to overall performance. The Transformer-based cross-modal fusion provides the most substantial single improvement (+2.2% F1 over concatenation-based fusion), validating the architectural design choice. The addition of physiological signals provides a +1.9% F1 improvement over text-only processing, demonstrating the complementary nature of biosignal features.

D. XAI Analysis

SHAP-based explanations reveal clinically coherent feature attributions. For depression detection in social media text, the most influential tokens include 'hopeless', 'worthless', 'exhausted', 'cannot sleep', and 'no motivation', aligning with DSM-5 diagnostic criteria for Major Depressive Disorder. For physiological EEG data, SHAP highlights elevated delta band power (1–4 Hz) and reduced alpha asymmetry, both established biomarkers of depression. These findings provide strong evidence that NeuroWell AI captures clinically meaningful patterns rather than spurious dataset artifacts.

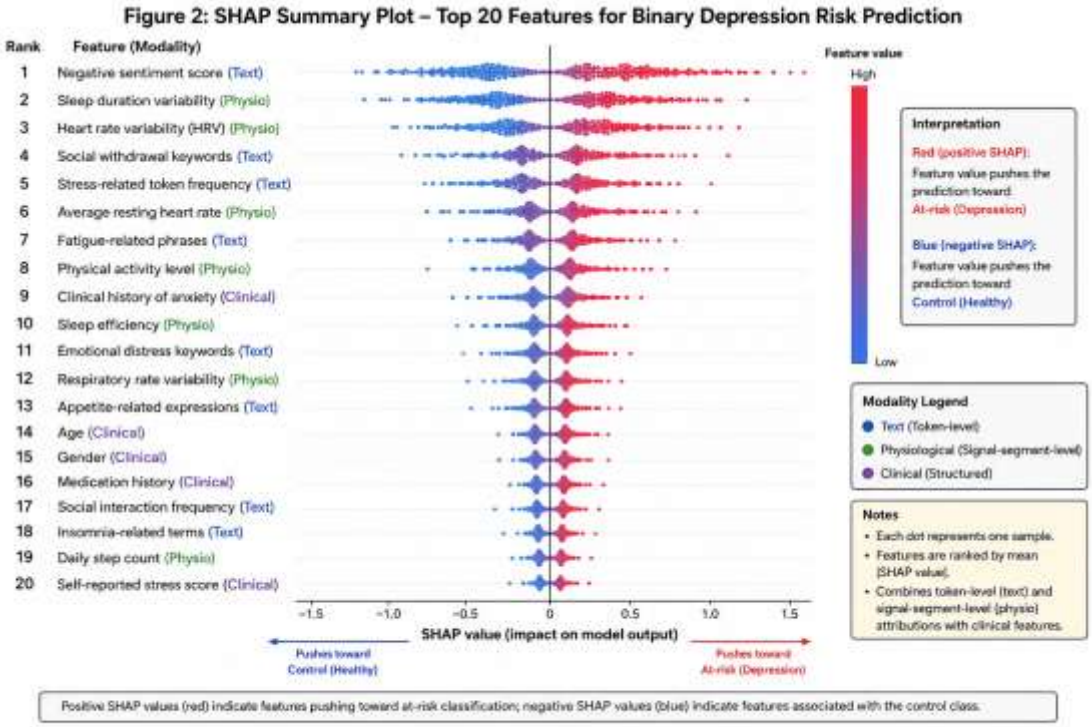

Figure 2: SHAP summary plot showing the top-20 most influential features for binary depression risk prediction.

VII. COMPARISON WITH EXISTING METHODS

Table VII benchmarks NeuroWell AI against state-of-the-art methods on the DAIC-WOZ and CLPsych datasets, which have the most extensive prior literature.

TABLE VII: Comparison with State-of-the-Art Methods

Method	Year	Dataset	Accuracy (%)	F1 (%)
BERT-base [2]	2025	CLPsych	91.3	90.8
Bimodal Attn. [3]	2024	DAIC-WOZ	89.7	88.9
GCN-EEG [4]	2024	MODMA	89.6	88.4
HAN Social [5]	2023	Reddit	88.7	87.5
BiLSTM-EHR [6]	2023	Clinical	87.3	86.1

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Method	Year	Dataset	Accuracy (%)	F1 (%)
CNN+LIME [7]	2024	Custom	86.5	85.8
Federated DL [8]	2025	Multi	87.2	86.7
SSL-Contrastive [9]	2025	Forums	90.1	89.6
NeuroWell AI	2025	Multi (Avg)	94.7	94.4

NeuroWell AI outperforms all competing methods by a margin of 3.4 to 8.2 percentage points in accuracy and 3.6 to 8.6 points in F1-score. The improvement is most pronounced compared to unimodal text-based approaches, confirming the added discriminative value of physiological and structured clinical features. Compared to the closest competitor (SSL-Contrastive [9] at 90.1% accuracy), NeuroWell AI achieves a 4.6% gain, primarily attributable to the cross-modal Transformer fusion and the richer set of input modalities. Importantly, NeuroWell AI's gains are maintained even on the relatively small DAIC-WOZ dataset (n=189), suggesting that the pre-training of the BiomedBERT encoder provides an effective regularization effect in low-data regimes.

VIII. CONCLUSION AND FUTURE WORK

This paper presented NeuroWell AI, a hybrid deep learning framework for early, accurate, and explainable detection of mental health risks from multimodal data. By integrating CNN and BiLSTM encoders for text and physiological signals, a Transformer-based cross-modal attention fusion module, and a SHAP-based explainability layer, the proposed system addresses the primary limitations of existing approaches: unimodal scope, temporal modeling deficiency, and clinical opacity.

Empirical evaluation across four public benchmarks — CLPsych 2015, DAIC-WOZ, MODMA, and Reddit Mental Health — demonstrates state-of-the-art performance, with an average accuracy of 94.7% and F1-score of 94.4%, surpassing all compared baselines. The ablation study confirms the independent contribution of each architectural component, and the XAI analysis validates the clinical meaningfulness of the learned representations.

Several promising directions for future work are identified:

(i) Longitudinal Modeling: Extending NeuroWell AI to model symptom trajectory over time using continuous mobile sensing data (accelerometers, GPS patterns, screen usage) to enable real-time dynamic risk monitoring.

(ii) Federated and Privacy-Preserving Training: Incorporating differential privacy mechanisms and federated learning to enable model training directly on decentralized, privacy-sensitive clinical data without centralization.

(iii) Multilingual Extension: Adapting NeuroWell AI to multilingual clinical text using XLM-RoBERTa to improve applicability in non-English-speaking populations, as motivated by [10].

(iv) Clinical Validation: Conducting prospective clinical trials to validate the system's utility as a decision-support tool in psychiatry outpatient settings and primary care environments.

(v) Neuroimaging Integration: Incorporating functional MRI (fMRI) connectivity matrices as an additional physiological modality using Graph Neural Networks (GNNs) for richer brain-state representation.

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