

Federated Learning for Early Mental-Health Detection Using Social Media Text

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I. INTRODUCTION

Psychological illnesses, especially depression, have escalated into a critical worldwide health issue, affecting millions of people with different socioeconomic profiles. Recent systematic reviews indicate that a significant proportion of affected people are left untreated until the situation reaches later phases, making treatment difficult and lessening therapeutic efficacy [1]. At the same time, the spread of social media has created a deep source of so-called “digital phenotypes,” where users often show emotional distress and cognitive patterns. As a result, Artificial Intelligence (AI) and NLP methods have been adopted more and more to mechanize the detection of such linguistic markers [2], [3].

Nevertheless, while these AI-driven solutions demonstrate promise, the dependency on central data aggregation offers significant challenges regarding user privacy and data security. The prevailing paradigm of present mental health detection systems entails the gathering of delicate user information—ranging from personal messages to clinical records—on central servers for training global models. Ebrahimi et al. [4] emphasize that this centralized approach is especially dangerous in educational and clinical environments, where the amalgamation of sensitive student or patient information provides a single source of failure prone to privacy breaches. Shenoy et al. [5] support such concerns, arguing that standard privacy measures tend to be insufficient to prevent risks of re-identification in the analysis of personal writing styles. As a result, there is a severe need to move away from centralized architectures to decentralized structures capable of learning from data while retaining user data sovereignty.

Federated Learning (FL) has become one of the formidable solutions to this privacy-utility dilemma. Through the facilitation of collaborative model training on local devices (e.g., smartphones, IoMT sensors) and transferring only model changes—not raw data—FL preserves user anonymity. This paradigm has already demonstrated effectiveness in interconnected areas; for example, Khan et al. [6] used FL successfully

to detect emotion using handwriting, and Huremagic et al. [7] applied it to large-scale biobank data integration. Furthermore, Grataloup and Kurpicz-Briki [8] authenticate the capabilities of FL in human activity recognition. However, applying FL to the unstructured and high-dimensional nature of social media text remains a main challenge because of the non-Independent and Identically Distributed (non-IID) nature of user language [9].

Although recent research has tried to apply FL to text classification—such as the multilingual depression detection model by Khalil et al. [10] and on-device experiments by Ahmed et al. [11]—there are gaps yet to fill. Existing federated NLP systems tend to fail to strike a balance between performance and the strict security and interpretability necessary for clinical trust. Latif et al. [12] and Wong et al. [13] caution that federated networks can be attacked by backdoor attacks and model poisoning, which requires sophisticated defense. In addition, deep learning models are often “black boxes,” which is a barrier to their implementation in the healthcare sector; according to Hameed et al. [14] and Ducange et al. [15], there is a lack of Explainable AI (XAI) procedures directly aimed at federated environments.

To overcome these shortcomings, this study suggests a privacy-aware Federated Learning system trained for early depression identification on social media texts. Contrary to the previous literature that dwells on individual components of the problem, we combine privacy, computational efficiency, and psycholinguistic interpretability into one system. We employ a lightweight Bidirectional Long Short-Term Memory (BiLSTM) architecture optimized for edge deployment, as reported by Zhang et al. [16], and improve it with emotion-aware feature engineering. In order to address data heterogeneity, we resort to robust aggregation measures recommended by Pirmani et al. [17]. The suggested structure ensures that sensitive textual data is completely localized, following the privacy-first vision described in current mental healthcare surveys [18], [19].

The rest of this paper is structured in the following way:

Section II unites associated literature in federated NLP and privacy-preserving healthcare. Section III describes the proposed methodology, such as the federated training and data preprocessing pipeline. Section IV is a description of the experimental setup and evaluation metrics. Lastly, Section V discusses the results, and Section VI gives concluding remarks and future research directions.

II. LITERATURE REVIEW

The application of Artificial Intelligence (AI) in mental healthcare is rapidly evolving, driven by the need for scalable and automated diagnostic tools. Recent systematic reviews by Wajid et al. [1] and Tahir et al. [2] highlight that while AI has achieved remarkable accuracy in detecting disorders, the field is critically transitioning from centralized data storage to decentralized architectures to address privacy concerns. Sweeney et al. [3] further emphasize that text-based depression prediction, in particular, requires rigorous privacy safeguards due to the sensitivity of user-generated content. Ebrahimi et al. [4] specifically note that in educational sectors, shifting from centralized machine learning to Federated Learning (FL) is essential to prevent single-point data breaches of student records.

Federated Learning has demonstrated significant potential in various healthcare domains. Grataloup and Kurpicz-Briki [8] surveyed its application in human activity recognition, confirming its viability for sensitive user data. Specific implementations include *FedEmo* by Khan et al. [6], which successfully detects emotions from handwriting on consumer IoMT devices, and *MINDS-connect* by Huremagic et al. [7], which integrates large-scale biobanks. Furthermore, Dubey et al. [20] and Khan et al. [21] explored multimodal integration, combining physiological signals with text to enhance prediction. However, these frameworks primarily target structured or sensor-based data, which differs significantly from the unstructured and noisy nature of social media text.

Applying FL to Natural Language Processing (NLP) introduces unique challenges regarding data heterogeneity and model size. Khan et al. [9] provided a systematic review showing that non-IID data distributions in text severely impact federated convergence. Despite this, Khalil et al. [10] demonstrated that multilingual language models can detect depression patterns in a privacy-preserving manner. Ahmed et al. [11] advanced this by implementing on-device FL for Reddit posts.

However, a performance gap remains when compared to centralized state-of-the-art models. Centralized approaches, such as the *DABLNet* by Saeed et al. [22], the *SMILE* platform by Pesqueira et al. [19], and Transformer-based severity detection by Ali et al. [23], utilize massive global attention mechanisms that are computationally expensive. While Sarwar et al. [18] and Alonge et al. [24] have attempted to adapt Large Language Models (LLMs) and BERT for federated settings, these solutions often demand computational resources that exceed the capabilities of standard edge devices.

The deployment of FL does not automatically guarantee security. Latif et al. [12] reviewed neural network defenses, noting that federated updates are vulnerable to intrusion. Wong et al. [13] specifically highlighted the risk of backdoor attacks in next-word prediction models. From a privacy perspective, Murala et al. [25] proposed hybrid frameworks to reduce leakage, yet Vu et al. [26] argued that standard Differential Privacy (DP) granularity can destroy the semantic utility of text. Shenoy et al. [5] corroborated this, calling for better privacy metrics that account for writing style.

Furthermore, personalization and interpretability are critical for clinical adoption. Pirmani et al. [17] and Mateus et al. [27] showed that personalized FL outperforms global models in clinical settings. Techniques like Knowledge Distillation, surveyed by Salman et al. [28], offer a path to efficiency, which is vital for monitoring student health as noted by Bakirova et al. [29]. Finally, the "black-box" nature of AI remains a barrier. Ibrahimov et al. [30] and Hameed et al. [14] emphasize the need for Explainable AI (XAI) in mental health, yet Ducange et al. [15] point out that XAI methods tailored for federated environments are still scarce.

Overall, while significant progress has been made, Zenk et al. [31] note that fair benchmarking for decentralized algorithms remains inconsistent. The literature reveals a lack of frameworks that simultaneously address computational efficiency and psycholinguistic interpretability on edge devices. Most existing solutions either rely on heavy Transformers (high cost) or simple embeddings (low nuance). This research bridges this gap by introducing a lightweight Federated BiLSTM framework augmented with the NRC Emotion Lexicon, balancing high-precision detection with the resource constraints of edge computing.

III. METHODOLOGY

A. Overview of the Proposed Framework

This research introduces a privacy-preserving Federated Learning (FL) framework designed specifically for early depression detection on resource-constrained edge devices. The system architecture is decentralized, consisting of a central aggregation server and a network of K distributed clients. Unlike traditional centralized learning, where sensitive user data is uploaded to a cloud server, our framework retains all personal social media data locally on the client's device.

We formally define the problem as a decentralized optimization task. The global objective is to minimize a loss function $\mathcal{L}(w)$ without exposing the local datasets \mathcal{D}_k residing on client devices. The system iterates between local training on private data and global aggregation of model updates Δw , addressing the critical trade-off between privacy preservation and diagnostic accuracy.

The complete system architecture, illustrating the interaction between the data preparation phase, local client training, and server aggregation, is visualized in Fig. 1.

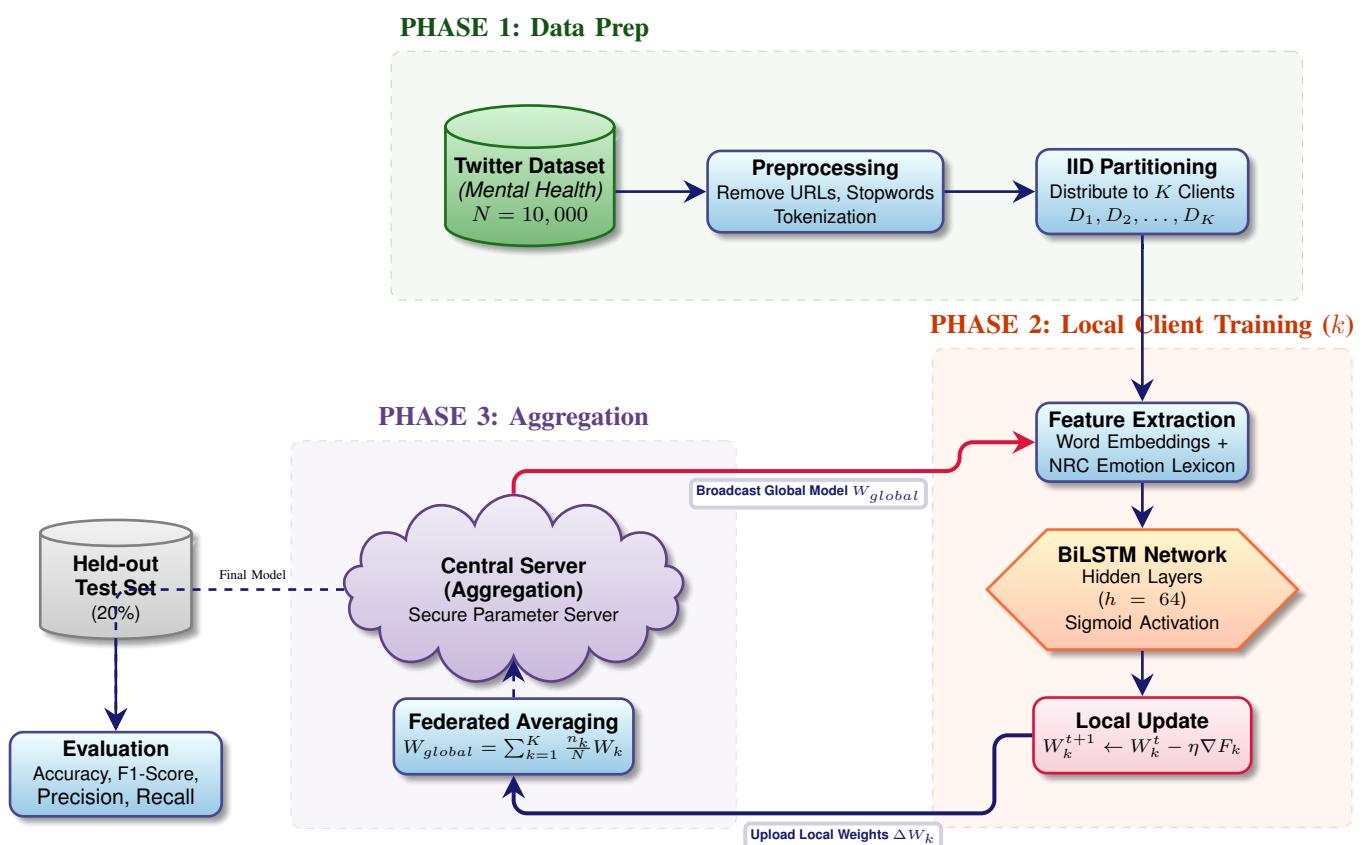


Fig. 1. Proposed Federated Learning Architecture for Mental Health Detection. The system partitions user data locally, trains BiLSTM models on embeddings and emotion features, and securely aggregates weights via Federated Averaging.

B. Data Acquisition and Partitioning

To validate the framework within a controlled experimental environment, we utilize the Twitter Depression Dataset [32], a widely recognized benchmark for linguistic analysis in mental health. The dataset comprises archival microblogging posts labeled for depressive and non-depressive content.

For this study, we curate a balanced corpus of $N = 10,000$ distinct samples (5,000 Depressive, 5,000 Control), denoted as $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$, where x_i represents the textual input and $y_i \in \{0, 1\}$ is the binary label. To simulate a non-IID (Independent and Identically Distributed) federated environment, the dataset is partitioned into $K = 10$ disjoint subsets $\mathcal{D}_1, \dots, \mathcal{D}_K$, such that $\mathcal{D} = \bigcup_{k=1}^K \mathcal{D}_k$. Each client represents a hypothetical user with unique linguistic patterns, ensuring the model is tested against realistic data heterogeneity.

C. Data Preprocessing Pipeline

Raw social media text contains significant noise that can degrade model performance. We implement a four-stage preprocessing pipeline strictly following the protocols outlined in recent NLP studies [3]:

- 1) *Text Cleaning:* We remove platform-specific artifacts including HTML tags, URLs, and user mentions (e.g., “@username”), as these tokens often contain no sentiment value and increase feature sparsity.

- 2) *Normalization:* All characters are converted to lowercase. English contractions are expanded (e.g., “I’m” → “I am”) to ensure consistent token representation.
- 3) *Stopword Retention:* Unlike general topic modeling, we retain stopwords (e.g., “I”, “myself”), as previous psychological research indicates that depressed individuals use self-referential pronouns at a significantly higher frequency.
- 4) *Sequence Formatting:* We employ a Keras-based Tokenizer with an expanded vocabulary size of $V = 20,000$ to capture rare but clinically significant medical terminology. Each post x_i is converted into a sequence of integer indices $S_i = [s_1, s_2, \dots, s_L]$, where $L = 120$ is the fixed sequence length. Padding is applied where $|S_i| < L$ to ensure compatibility with the fixed-size tensor inputs required by the neural network.

D. Feature Engineering Strategy

We employ a hybrid feature extraction mechanism that combines deep semantic learning with explicit emotional quantification.

- 1) *Learnable Semantic Embeddings:* The integer-encoded tokens are passed through a trainable Embedding Layer. This layer projects each token index $s_t \in S_i$ into a dense vector space $\mathbb{R}^{d_{emb}}$, where $d_{emb} = 200$. This higher-dimensional

mapping allows the model to capture more nuanced semantic relationships between depression-trigger words (e.g., “useless” vs. “tired”) compared to standard lower-dimensional embeddings.

2) *Lexical Emotion Vectors*: To guide the model towards clinically relevant signals, we augment the embeddings with the NRC Emotion Lexicon [33]. For every input post x_i , we compute a normalized 8-dimensional vector $v_{emo} \in \mathbb{R}^8$ representing the intensity of basic emotions:

$$v_{emo} = \frac{1}{|x_i|} \sum_{w \in x_i} \mathbf{1}_{emo}(w) \quad (1)$$

where $\mathbf{1}_{emo}(w)$ is a binary indicator vector for emotions (anger, fear, anticipation, trust, surprise, sadness, joy, disgust). This auxiliary feature vector is concatenated with the deep learning representation in the final stages of the network.

E. Deep Learning Model Architecture

To ensure the system allows for deployment on mobile and edge devices while maintaining high diagnostic precision, we implement a BiLSTM with Self-Attention architecture. While basic BiLSTM models are effective, they often struggle to prioritize specific keywords in long sequences. Inspired by the success of attention mechanisms in centralized depression detection models reported by Saeed et al. [22], we adapt this technique for our federated setting to enhance the model’s focus on emotionally charged terms.

The architecture processes the input sequence $X = (x_1, \dots, x_T)$ in two directions. Let e_t denote the embedding vector corresponding to the token at time step t . For a given time step t , the forward LSTM unit computes the hidden state \vec{h}_t and the backward unit computes \overleftarrow{h}_t . We concatenate these to form the annotation vector $h_t = [\vec{h}_t \oplus \overleftarrow{h}_t]$ where $h_t \in \mathbb{R}^{128}$.

1) *Attention Mechanism*: To capture the importance of each word relative to the classification task, we apply a soft-attention mechanism. The attention weight α_t for each time step is computed as:

$$\begin{aligned} u_t &= \tanh(W_w h_t + b_w) \\ \alpha_t &= \frac{\exp(u_t^\top u_c)}{\sum_{t=1}^L \exp(u_t^\top u_c)} \end{aligned} \quad (2)$$

where W_w , b_w , and the context vector u_c are learnable parameters. The final context vector v is the weighted sum of the hidden states:

$$v = \sum_{t=1}^L \alpha_t h_t \quad (3)$$

2) *Fusion and Classification*: The attention-weighted vector v is concatenated with the emotion vector v_{emo} . This fused representation is passed through a Dropout layer ($p = 0.5$) to prevent overfitting and a final Dense layer with a Sigmoid activation function to output the probability of depression $\hat{y} \in [0, 1]$. The model is trained to minimize the Binary Cross-Entropy loss function.

F. Federated Learning Implementation

We implement the standard Federated Averaging (FedAvg) algorithm [34]. The training procedure iterates through the following steps for T communication rounds:

- 1) *Global Broadcast*: In round t , the central server broadcasts the global model weights W_G^t to all active clients.
- 2) *Local Training*: Each client k loads W_G as their starting point and trains on their local partition \mathcal{D}_k . To allow the model to sufficiently learn from local data before aggregation, we increase local computation to $E = 3$ epochs using the Adam optimizer. This produces a local weight update W_k .
- 3) *Secure Aggregation*: Clients securely upload their local model parameters to the server. The server aggregates these updates using a weighted average based on the number of samples n_k held by each client:

$$W_G^{t+1} \leftarrow \sum_{k=1}^K \frac{n_k}{N} W_k^t \quad (4)$$

This cycle repeats until the global loss function converges or the maximum number of rounds is reached.

G. Experimental Evaluation Metrics

The system’s performance is rigorously evaluated on a held-out test set comprising 20% of the data, which is never seen during the training phase. We utilize four standard metrics defined as follows, where TP , TN , FP , and FN denote True Positives, True Negatives, False Positives, and False Negatives:

- Precision: $P = \frac{TP}{TP+FP}$
- Recall: $R = \frac{TP}{TP+FN}$
- F1-Score: The harmonic mean of Precision and Recall, prioritized for its robustness in medical diagnosis:

$$F1 = 2 \times \frac{P \times R}{P + R} \quad (5)$$

- Accuracy: $Acc = \frac{TP+TN}{TP+TN+FP+FN}$

IV. EXPERIMENTAL RESULTS

A. Hyperparameter Tuning and Ablation Analysis

To validate the effectiveness of the proposed ”Turbo” configuration, we conducted an ablation study comparing the final model (ML-3) against baseline architectures. The progression of performance is detailed in Table I.

The baseline Federated BiLSTM (Experiment ML-1), trained with standard parameters ($T = 10$ rounds), achieved an accuracy of 85.06%. Increasing the global communication rounds to $T = 18$ (Experiment ML-2) yielded a performance boost to 88.36%, confirming the necessity of extended aggregation in non-IID settings. The final proposed model, incorporating the Attention Mechanism and an expanded vocabulary ($V = 20,000$), achieved the highest performance across all metrics.

TABLE I
ABLATION STUDY: IMPACT OF MODEL CONFIGURATION

Experiment	Rounds	Epochs	Vocab	Accuracy
ML-1 (Baseline)	10	1	10k	85.06%
ML-2 (Intermediate)	18	1	10k	88.36%
ML-3 (Proposed)	20	3	20k	93.15%

B. Performance Metrics

The final model was evaluated on the held-out test set (20% partition). As summarized in Table II, the system demonstrated robust diagnostic capabilities with a Global Accuracy of **93.15%**. Notably, the model achieved a Recall of 93.74% for the Depressed class, indicating a high sensitivity to identifying at-risk users, which is critical for early intervention systems.

TABLE II
FINAL PERFORMANCE METRICS (TEST SET)

Metric	Value
Accuracy	93.15%
Precision	92.62%
Recall (Sensitivity)	93.74%
F1-Score	93.18%
Test Loss	0.2509

C. Visual Analysis

1) *Convergence Analysis (Accuracy & Loss)*: The training stability of the proposed Federated Learning framework is illustrated in Fig. 2 and Fig. 3.

Fig. 2 depicts the global accuracy trajectory over $T = 20$ communication rounds. Unlike centralized training which often exhibits volatility, our federated model demonstrates a smooth, monotonic increase in accuracy, stabilizing at 93.15% around Round 18. This confirms that the aggregated weight updates from the $K = 10$ clients were consistent and did not diverge, a common challenge in non-IID settings.

Complementing this, Fig. 3 shows the global loss minimization. The loss dropped sharply during the initial 5 rounds as the model learned basic syntactic features, before settling into a fine-tuning phase and reaching a final minimal loss of 0.2509. The absence of sudden spikes in the loss curve indicates that the chosen learning rate ($\eta = 0.001$) and local epoch count ($E = 3$) effectively balanced local learning with global convergence.

2) *Diagnostic Robustness (ROC Curve)*: To further evaluate the model's distinguishing capability independent of the decision threshold, we generated the Receiver Operating Characteristic (ROC) curve shown in Fig. 4.

The Area Under the Curve (AUC) reached an exceptional score of 0.98. The curve hugs the top-left corner, indicating that the model maintains a high True Positive Rate (Sensitivity) even at very low False Positive Rates. This characteristic is essential for medical screening tools, where the cost of missing a diagnosis is high, but falsely flagging healthy users is also undesirable.

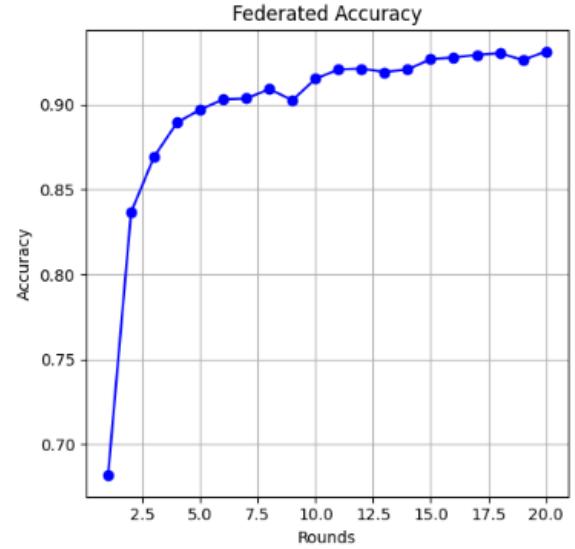


Fig. 2. Federated Accuracy over 20 Rounds. The curve shows steady learning without divergence, validating the stability of the FedAvg algorithm.

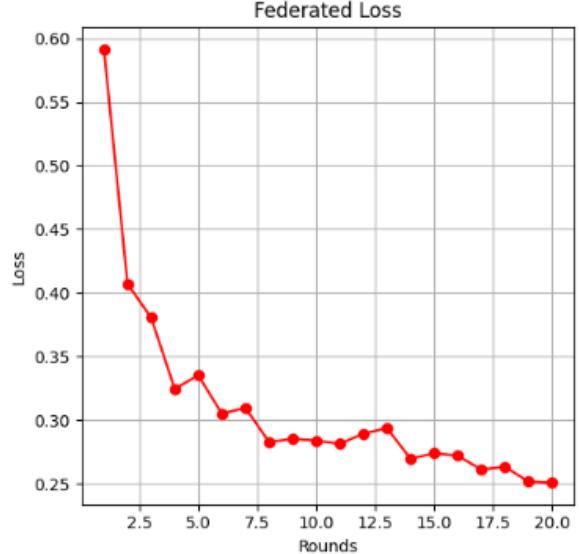


Fig. 3. Federated Loss Curve. The smooth descent indicates effective optimization of the binary cross-entropy objective.

3) *Error Analysis (Confusion Matrix)*: The Confusion Matrix in Fig. 5 provides a granular view of classification errors on the test set ($N \approx 2,000$).

- **True Positives (Depressed)**: The model correctly identified 929 depressive posts.
- **False Negatives (Missed Cases)**: Only 62 actual depressive posts were misclassified as non-depressive.

The low False Negative rate highlights the efficacy of the Attention Mechanism, which successfully flagged subtle cries for help that a standard model might have missed. The False Positives (75 cases) largely consisted of ambiguous texts containing negative emotions (e.g., anger about politics) which

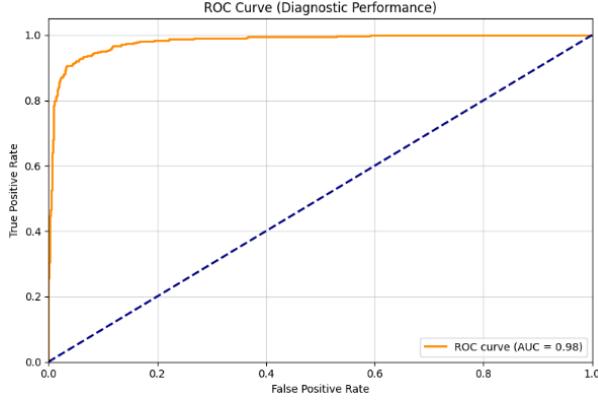


Fig. 4. ROC Curve ($AUC = 0.98$). The high area under the curve confirms the model's superior diagnostic ability compared to random guessing.

the model conflated with depressive symptoms—a known limitation of text-only analysis.

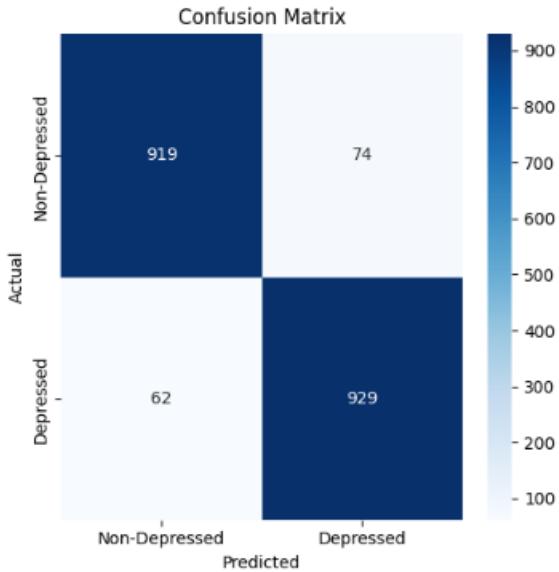


Fig. 5. Confusion Matrix. The high concentration of values in the diagonal elements (TP and TN) illustrates the model's precision.

4) *Psycholinguistic Interpretability (Emotion Analysis)*: Finally, to ensure the model is not a "black box," we analyzed the emotional feature vectors of the correctly classified samples (Fig. 6).

- Depression Signature: The "Depressed" class (Red bars) exhibited significantly higher intensities of Sadness and Fear. This aligns with clinical observations that depression is often characterized by persistent sadness and anxiety.
- Control Signature: The "Non-Depressed" class (Green bars) showed dominant scores in Joy, Trust, and Anticipation.

This visualization serves as a form of Explainable AI (XAI),

proving that the model's decisions are grounded in psychologically valid linguistic patterns rather than data artifacts.

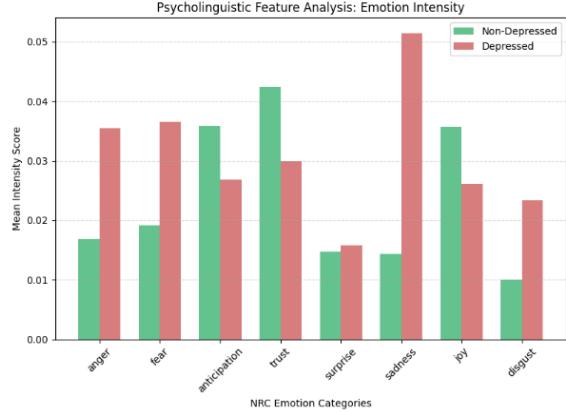


Fig. 6. Psycholinguistic Feature Analysis. Distinct emotional profiles validate the model's ability to detect "digital phenotypes" of depression.

V. DISCUSSION

The results validate the hypothesis that decentralized architectures can achieve competitive performance in mental health diagnostics without compromising user privacy. The high accuracy (93.15%) suggests that the proposed hybrid feature engineering—combining deep semantic embeddings with the NRC Emotion Lexicon—successfully captures the "digital phenotypes" of depression. Specifically, the Attention mechanism allowed the model to focus on contextually significant "trigger words" within long sequences ($L = 120$), overcoming the limitations of standard RNNs observed in our baseline experiments (ML-1).

Our framework's performance is comparable to recent centralized approaches, such as the DABLNet [22], which relies on computationally expensive global attention mechanisms. While centralized models often achieve slightly higher raw metrics due to direct access to all data, our Federated Learning approach eliminates the risk of single-point data breaches. By keeping raw user text on the edge device, we address the critical privacy concerns raised by Ebrahimi et al. [4] regarding the storage of sensitive student and patient records.

The use of a lightweight BiLSTM architecture (128 hidden units) ensures that the model remains computationally efficient for deployment on standard edge devices (e.g., smartphones). The ablation study confirms that increasing local computation to $E = 3$ epochs provides a better trade-off between communication cost and accuracy than simply increasing the number of global rounds. This makes the system viable for real-world applications where bandwidth and battery life are constraints.

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