Depression Detection on Social Media with Large Language Models

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Abstract

Limited access to mental healthcare resources hinders timely depression diagnosis, leading to detrimental outcomes. Social media platforms present a valuable data source for early detection, yet this task faces two significant challenges: 1) the need for medical knowledge to distinguish clinical depression from transient mood changes, and 2) the dual requirement for high accuracy and model explainability. To address this, we propose DORIS, a framework that leverages Large Language Models (LLMs). To integrate medical knowledge, DORIS utilizes LLMs to annotate user texts against established medical diagnostic criteria and to summarize historical posts into temporal *mood courses*. These medically-informed features are then used to train an accurate Gradient Boosting Tree (GBT) classifier. Explainability is achieved by generating justifications for predictions based on the LLM-derived symptom annotations and mood course analyses. Extensive experimental results validate the effectiveness as well as interpretability of our method, highlighting its potential as a supportive clinical tool.

1 Introduction

Depression is a major global health challenge, yet significant barriers like cost, stigma, and lack of infrastructure prevent many from receiving timely care, creating a critical treatment gap (Organization; Khan et al., 2016; Rüsch et al., 2005). To help bridge this gap, analyzing public social media data offers a scalable approach for early detection. By examining patterns in users' posts, data-driven systems can provide clinicians with timely signals of potential distress, augmenting traditional diagnostic methods (Orabi et al., 2018; Shen et al., 2017; Sarkar et al., 2022).

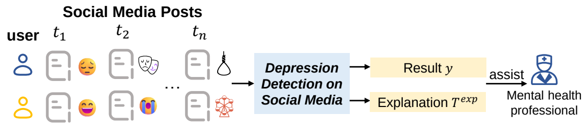

Figure 1: Depression detection on social media analyzes users' social media post history to identify potential depression, offering insights to support mental health professionals in depression assessment.

However, building a clinically valid and trustworthy system from this data presents significant hurdles. Many existing deep learning methods (Lin et al., 2020; Orabi et al., 2018; Sarkar et al., 2022) lack a systematic integration of medical knowledge, struggling to distinguish the complex patterns of clinical depression from transient sadness (Zhang et al., 2023a). Furthermore, they often function as "black boxes", failing to provide the transparent, evidence-based reasoning that clinicians require for validation and trust. While Large Language Models (LLMs) offer powerful interpretation capabilities (Yang et al., 2023a), their direct use for classification can lead to lower accuracy and reliability issues (Arcan et al., 2024; Hua et al., 2024). This reveals a critical need for a framework that synergistically combines clinical knowledge, robust prediction, and explainability.

To address these challenges, we propose DORIS (short for **D**ia-gn**O**stic C**R**iteria-Guided Mood H**IS**tory-Aware). For the first challenge, we leverage LLMs' strong language understanding capabilities to recognize complex expressions of depression symptoms based on DSM-5 criteria. We also systematically model users' mood courses by filtering emotionally intensive posts and using LLMs to analyze their temporal patterns, enabling holistic assessment of users' emotional fluctuations. For the second challenge, we design a hybrid approach that combines LLMs for explainable symptom and mood course analysis with GBT classifier for a robust final prediction. This design achieves high

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accuracy through the classifier while maintaining explainability in two ways: through concrete evidence derived from medical knowledge (annotated symptoms and mood courses), and through LLM-generated explanations that connect this evidence to depression assessment.

Our method shows significant improvements in experimental evaluation, achieving a 0.0361 gain in AUPRC over the current best baseline. Ablation studies validate each component's contribution, and case studies demonstrate the system's ability to generate explainable assessments backed by concrete evidence.

Our contributions can be summarized as follows:

- We propose a novel hybrid depression detection framework that synergistically combines a robust classifier for accurate prediction with an LLM for explainable, clinically-grounded feature generation, addressing the critical dual need for accuracy and interpretability.
- We introduce a methodology to systematically operationalize medical knowledge by using LLMs for both fine-grained DSM-5 symptom annotation and longitudinal mood course analysis, creating features that align closely with clinical diagnostic practices.
- We demonstrate through extensive experiments on real-world data that our approach not only significantly improves detection performance but also provides clinically interpretable explanations grounded in medical knowledge, demonstrating a viable pathway for creating practical AI-driven tools that support clinicians and improve mental healthcare access in low-resource settings.

2 Methodology

2.1 Problem Formulation

This study addresses the task of depression detection based on users' social media posts. Users often use posts to document events around them and express their feelings, making these candid expressions valuable for gauging the likelihood of depression. Given a user u, let $P = \{p_1, p_2, ..., p_n\}$ denote their historical posts with the corresponding timestamps $\{t_1, t_2, ..., t_n\}$. Our objective is to learn a mapping function $f : P \rightarrow y$ that predicts the depression status $y \in \{0, 1\}$ of user u, where $y = 1$ indicates the presence of depression and $y = 0$ indicates its absence.

In the following part, we describe our proposed DORIS in detail. The architecture of DORIS is illustrated in Figure 2.

2.2 Diagnostic Criteria Feature Extraction

2.2.1 Annotation with LLM

Clinical practice offers well-established diagnostic frameworks for depression that have proven highly effective in professional assessment. To bring this medical expertise to social media-based detection, we incorporate standardized diagnostic criteria into our system's design. Specifically, we utilize DSM-5 (Regier et al., 2013), a widely recognized diagnostic tool in psychiatry that provides comprehensive criteria for mental disorder assessment and diagnosis. The core criteria in DSM-5, which guide mental health professionals in their diagnostic practice, are detailed in Table 1.

Table 1: A concise summary of the symptoms of depression as defined in the DSM-5. To be diagnosed with depression, five (or more) of the listed symptoms must be present during the same two-week period.

A. Depressed mood
B. Loss of interest/pleasure
C. Weight loss or gain
D. Insomnia or hypersomnia
E. Psychomotor agitation or retardation
F. Fatigue
G. Inappropriate guilt
H. Decreased concentration
I. Thoughts of suicide

Prior attempts to integrate clinical standards via DSM-5 criteria or its simplified screening tool PHQ-9 (Yadav et al., 2020; Nguyen et al., 2022; Zhang et al., 2023a) rely on simple classification models that struggle to comprehend complex symptom expressions in social media texts. The emergence of large language models (LLMs) offers a promising solution to this challenge. LLMs exhibit a remarkable capacity for semantic understanding (Achiam et al., 2023), and research has demonstrated their potential to replace human annotators in certain tasks (Ziems et al., 2023). Here, we employ LLMs to accurately annotate texts, specifically to identify if and which self-expressed symptoms of depression are present in posts. The prompt is described in Appendix F.

By post-processing the output from the LLM, we can generate a 9-dimensional vector for each post, with each element being 0 or 1, indicating the absence or presence of a specific depression

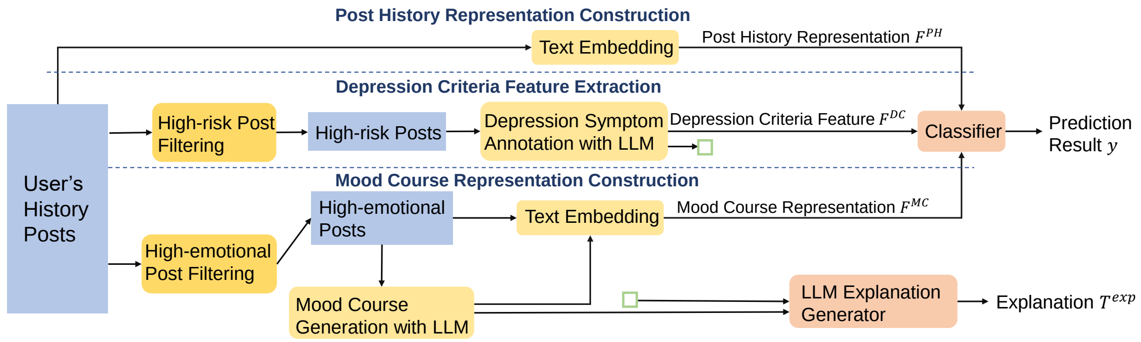

Figure 2: Illustration of DORIS. Through the collaboration of the LLM and the text embedding model, we obtain three key features: depression symptom feature, post history representation, and mood course representation. The classifier uses these three features to make its judgment; the LLM uses annotations of depression symptoms and descriptions of the mood course to generate explanation for the system's decision.

symptom. For instance, if the output for a post p is *(G, I)*, then the corresponding vector E_p would be $(0,0,0,0,0,0,1,0,1)$.

2.2.2 Efficient Annotation.

The use of LLMs incurs substantial financial and energy costs. Since the vast majority of posts on social media platforms are unrelated to depression, annotating all posts would be exceedingly wasteful. To address this issue, we design an efficient annotation approach that first filters for high-risk texts through carefully validated symptom templates (detailed in Appendix G) and then annotates only those texts with LLMs. We developed symptom templates through a four-stage process. First, psychiatrists created initial templates from DSM-5 diagnostic criteria. Second, we refined them using a corpus of 500 social media posts independently annotated by four clinicians, evaluating inter-annotator agreement (Cohen's kappa) to improve them. Third, experts iteratively reviewed the templates for clinical accuracy and coverage until reaching consensus. Finally, experimental validation confirmed that filtering with our templates achieves comparable performance to full LLM annotation at a significantly lower computational cost.

Then, we get the text embedding of all symptom templates using a text embedding model:

$$H_i = \text{Encoder}(T_i^{DC}), \text{for } i = \text{A to I}. \quad (1)$$

For each post p, we compute its embedding as :

$$H_p = \text{Encoder}(p). \quad (2)$$

Next, we calculate the average similarity between post p and each symptom template:

$$Sim_p = \text{mean}(Sim(H_p, H_i)), \text{for } i = \text{A to I}, \quad (3)$$

where Sim_p represents the depression risk level of post p. We only use the LLM to annotate posts with the top $k\%$ of Sim_p scores, while the depression symptom vector E_p for all other posts is directly set to a zero vector. Here k is a hyperparameter. Finally, for each user u, we average all their depression symptom vectors to obtain their diagnostic criteria feature F_u^{DC}:

$$F_u^{DC} = \frac{1}{N}\sum_{p=1}^{N} E_p, \quad (4)$$

where N is the total number of posts by user u.

2.3 Mood Course Representation Construction

The mood course, also termed mood trajectory in clinical literature, represents the temporal pattern and progression of emotional states (Cochran et al., 2016) and is critical in diagnosing clinical depression (Costello et al., 2002). It delineates the onset, duration, and recurrence of mood episodes, providing insights into the disorder's nature and trajectory (Frías et al., 2017). Accurately modeling mood course is pivotal for distinguishing depressive disorders from transient mood fluctuations, facilitating early detection and appropriate intervention (Rudolph et al., 2006). However, former works on depression detection have largely overlooked the mood course, focusing instead on static mood snapshots. Our study bridges this gap by explicitly modeling mood course and integrating it into our classification system. Next, we detail our approach.

2.3.1 Posts Filtering

Not all posts are emotionally charged. We begin by filtering posts with a high emotional content.

Following Oatley and Johnson-Laird (1987), we categorize emotions into five main types: 1) anger, 2) disgust, 3) anxiety, 4) happiness, and 5) sadness. For each of these emotional categories, with the help of professional psychologists, we establish a template of emotional expressions (detailed in Appendix H) using the same systematic four-stage process described for depression symptom templates. For instance, the template for sadness, T_5^E, is defined as:

> *"I am sad, sorrowful, melancholic, in pain, lost, depressed, pessimistic, tearful, grieving, mournful, depressed, suicidal, heartbroken, devastated, upset, crying, deeply saddened, disconsolate, dejected, lamenting, desolate, gloomy, mournful, weeping bitterly, desperate, heartbroken, indignant."*

For each emotion template, we generate a representation using a pre-trained embedding model:

$$H_j^E = \text{Encoder}(T_i^E), \text{for } j = 1, 2, ..., 5. \quad (5)$$

2.3.2 Representation Construction

For each post p, we obtain its embedding H_p. We calculate the similarity between post p and each emotion template as:

$$Sim_{pj} = Sim(H_p, H_j), \text{for } j = 1, 2, ..., 5. \quad (6)$$

For each emotion j, we retain posts within the top $m\%$ of similarity, forming the set S_j. Here m is a hyperparameter. The final set of posts with high emotional content, S, is the union of all S_j.

For each user u, we intersect their historical post set P_u with the high emotional content set S to obtain P_u^E. Based on this subset of emotionally expressive posts, we use an LLM to synthesize a description of user u's mood course, T^{MC}, the prompt is described in Appendix F.

We then compute the embedding of T^{MC}:

$$H^{MC} = \text{Encoder}(T^{MC}). \quad (7)$$

The user u's mood course representation F_u^{MC} is computed as:

$$F_u^{MC} = \alpha H^{MC} + \beta \frac{1}{|P_u^E|} \sum_{p \in P_u^E} H_p, \quad (8)$$

where $\left|P_u^E\right|$ is the total number of posts in P_u^E, and α, β are hyperparameters. Here we get F_u^{MC} as a comprehensive representation of the types and evolution of user historical moods.

2.4 Post History Representation Construction

In the sections above, we construct the diagnostic criteria feature and mood course representation from users' historical posts through filtering and labeling. While these filtering steps emphasize aspects crucial for medical diagnosis of depression, they may also result in information loss. To address this, we construct a representation of the user's post history as follows:

$$F^{PH} = \frac{1}{N} \sum_{p=1}^{N} H_p, \quad (9)$$

where H_p is the embedding of the p-th post, and N is the total number of posts by the user.

2.5 Training and Predicting

In this section, we describe our training and predicting methodology. First, we integrate the various features. F^{MC} and F^{PH}, which shares the same space, are directly summed to avoid increasing the dimension and exacerbating the risk of overfitting. Conversely, F^{DC} resides in a distinct space, and thus we concatenate this feature with the sum of the first two parts. The final feature vector F is obtained as:

$$F = \text{Concat}\left(F^{MC} + F^{PH}, F^{DC}\right) \quad (10)$$

We employ Gradient Boosting Trees (GBT) for classification. GBT is an ensemble learning method that constructs a sequence of decision trees, where each subsequent tree aims to correct the errors of its predecessor. It excels in automatically performing feature interactions by selecting optimal split criteria within its decision trees, thus effectively fusing the components of F. The final prediction, denoted as y, is a binary classification result derived from the ensemble model. The process is formalized as follows:

First, the ensemble model G is initialized and then enhanced iteratively by adding decision trees:

$$G_m(x) = G_{m-1}(x) + \nu \cdot h_m(x). \quad (11)$$

Each tree $h_m(x)$ is fitted to the negative gradient of the loss function evaluated at G_{m-1}, aiming to minimize:

$$\sum_{i=1}^{N} L\left(y_i, G_{m-1}\left(x_i\right) + h_m\left(x_i\right)\right). \quad (12)$$

The prediction y is given by the sign of $G_M(x)$, the output after M iterations:

$$y = \operatorname{sign}\left(G_M(x)\right). \tag{13}$$

Here, L represents the loss function, N is the number of samples, M is the total number of trees, and ν is the learning rate.

Furthermore, for safety-critical tasks with severe class imbalance like depression detection, ensuring the model's output probabilities are reliable is crucial. The raw scores from a GBT model may be miscalibrated. To address this, a post-processing calibration step can be applied to improve clinical utility. Methods like Isotonic Regression can adjust the classifier's scores to better reflect true posterior probabilities. This helps correct for potential biases, such as underestimating the probability of the minority class, thereby providing clinicians with more trustworthy confidence scores.

2.6 Design for Explainability

Explainability is critical for safety-sensitive tasks like depression detection (Zhang et al., 2022). While Large Language Models (LLMs) show potential for generating interpretable analysis (Yang et al., 2023a,b), their direct use for classification can be unreliable and sensitive to prompting (Hua et al., 2024). Our hybrid approach is explicitly designed to overcome this by combining a robust traditional classifier with the interpretive power of an LLM, leveraging the strengths of both.

Our system's explainability is two-fold. First, the final prediction is based on two clinically-relevant, human-readable features generated by an LLM: 1) a set of annotated symptoms aligned with DSM-5 criteria, and 2) a narrative summary of the user's longitudinal "mood course". These features serve as direct evidence for the model's reasoning. Second, to synthesize this evidence for the end-user, the system uses an LLM to generate a final explanatory text, T^{Exp}, that explicitly connects the identified symptoms and mood patterns to the classification result (y). The prompt used for this generation is detailed in Appendix F.

3 Experimental Setup

3.1 Implementation Details

Following Orabi et al. (2018), we utilize cosine similarity to calculate the similarity between embeddings. To enhance the usability of our method in low-compute resource settings, we employ a low-resource-demanding pre-trained text embedding model, gte-small (Li et al., 2023), which operates smoothly with just 1GB of memory. The text embedding model in our system can easily be switched to other higher-performance models to further improve performance. For the LLM, we use GPT-4o mini [1], which requires only an internet connection to interact with it through the API service provided by OpenAI. We have verified that OpenAI's terms of service prohibit storing or retaining any user-provided text data, ensuring data privacy. The LLM in our system can also be substituted with open-source models deployed locally, such as Mentallama (Yang et al., 2023b), to further ensure data privacy. Overall, our system can run at low computational costs, enhancing its accessibility. We utilize XGBoost (Chen and Guestrin, 2016) for an efficient implementation of Gradient Boosting Trees. We run each experiment 5 times and report the average performance across these runs.

3.2 Dataset

Our primary study utilizes a cohort from the ethically-sourced SWDD dataset (Cai et al., 2023), consisting of **1,000** expert-identified depressed users and **19,000** control users to reflect a real-world 1:19 prevalence ratio. Following best practices (Eichstaedt et al., 2018) and accommodating model constraints, we retained only the final six months of each user's post history. This resulted in a corpus of approximately 70k posts from the depressed group and 1.3M from the control group. To further validate the generalizability of our approach, we also conducted experiments on the Twitter Mental Disorder dataset [2]. For a more detailed description of the datasets, please refer to Appendix B.

3.3 Baseline Methods

We employ various baselines, including methods combining traditional feature extraction with classifiers: TF-IDF+XGBoost (Ramos et al., 2003; Chen and Guestrin, 2016; Wu et al., 2023), deep learning approaches: HAN (Yang et al., 2016), Mood2Content (Cai et al., 2023), and AMM-Net (Sarkar et al., 2022), PLM-based methods: FastText (Joulin et al., 2016), BERT (Devlin et al., 2018), gte-small (Li et al., 2023) and Mental-

[1] https://platform.openai.com/docs/models/GPT-4o-mini

[2] https://www.kaggle.com/datasets/rrmartin/twitter-mental-disorder-tweets-and-musics.

Table 2: Performance of DORIS and baselines on the SWDD dataset. The best scores are in bold, and second best scores are underlined.

Category	Method	Precision	Recall	F1-score	AUROC	AUPRC
Traditional Method	TF-IDF+XGBoost	0.3644	0.4312	0.3945	0.9023	0.4303
Deep Learning-Based Methods	HAN	0.5702	0.6524	0.6075	0.8929	0.5864
	Mood2Content	0.7216	0.6996	0.7106	0.9537	0.7774
	AMM-Net	0.6851	0.6861	0.6856	0.9220	<u>0.7786</u>
PLM-Based Methods	FastText	<u>0.7467</u>	0.5586	0.6421	0.9441	0.6255
	gte-small	0.7359	0.6524	0.6916	0.9499	0.6959
	BERT	0.6667	0.6294	0.6531	0.9481	0.7102
	MentalRoBERTa	0.7326	0.6272	0.6774	0.9423	0.6880
Medical Knowledge-Guided Methods	PHQ9 (Score)	0.7137	0.6974	<u>0.7055</u>	<u>0.9522</u>	0.7703
	PHQ9 (Vector)	0.7221	0.6852	0.7032	0.9479	0.7631
LLM-Based Methods	GPT-4o mini	0.0895	0.7122	0.1590	0.6603	0.0767
	MentalLLama	0.0899	<u>0.7780</u>	0.1612	0.6821	0.0811
Our Method	DORIS	**0.7606**	**0.7902**	**0.7750**	**0.9722**	**0.8147**

RoBERTa (Ji et al., 2023), medical knowledge-guided methods: PHQ9 (Score) and PHQ9 (Vector) (Nguyen et al., 2022), as well as LLM-based methods like MentalLLama (Yang et al., 2023b) and GPT-4o mini. A more detailed description of comparison methods is in Appendix C.

3.4 Evaluation Metrics

Following prior works, we evaluate our method using five metrics: Precision, Recall, F1, AUROC, and AUPRC. AUPRC can be considered as the most important metric, as it best reflects the classifier's performance on highly imbalanced datasets (Davis and Goadrich, 2006).

4 Experimental Analysis

We conducted extensive experiments to address the following research questions:

- **RQ1:** How does our proposed system, DORIS, perform on the depression detection task compared to state-of-the-art methods?
- **RQ2:** How effective is DORIS at generating clinically relevant and evidence-based explanations for its predictions?
- **RQ3:** To what extent does each component of DORIS contribute to its overall performance?
- **RQ4:** How do key hyperparameter settings impact the performance of our method?

Due to space constraints, we present the experimental results for RQ4 in the Appendix.

4.1 Overall Performance (RQ1)

The results in Table 2 demonstrate the superiority of our approach on the SWDD dataset. DORIS outperforms all baselines across all metrics, achieving an absolute improvement of 0.0361 in AUPRC over the strongest baseline, AMM-Net. This performance gain stems from our hybrid design, which addresses the weaknesses of alternative methods.

Our experiments confirm that directly using LLMs like GPT-4o mini for classification leads to poor performance, exhibiting high recall but very low precision. Furthermore, while other methods incorporate medical knowledge (e.g., PHQ9-based models), their reliance on less capable backbones like BERT limits their ability to understand complex symptom descriptions. In contrast, DORIS leverages a powerful LLM to effectively model clinical criteria and mood courses. By using the LLM for sophisticated, clinically-grounded feature engineering rather than direct prediction, our task-specific design effectively combines the strengths of modern language models and robust classifiers, leading to state-of-the-art results.

We also conduct experiments on the Twitter Mental Disorder dataset to further validate the effectiveness and generalizability of DORIS. The results are presented in Table 3.

Table 3: Performance comparison on the Twitter Mental Disorder Dataset.

Model	F1-score	AUROC	AUPRC
TF-IDF+XGBoost	0.9156	0.7149	0.9675
FastText	0.9189	0.7879	0.9770
Mood2Content	0.9101	0.8112	0.9775
gte-small	0.9028	0.8089	0.9812
BERT	0.9211	0.7581	0.9753
MentalRoBERTa	0.9211	0.8143	0.9824
DORIS	**0.9296**	**0.8647**	**0.9878**

As the results show, DORIS consistently outperforms strong baselines on this additional dataset across all metrics. This reinforces the findings from

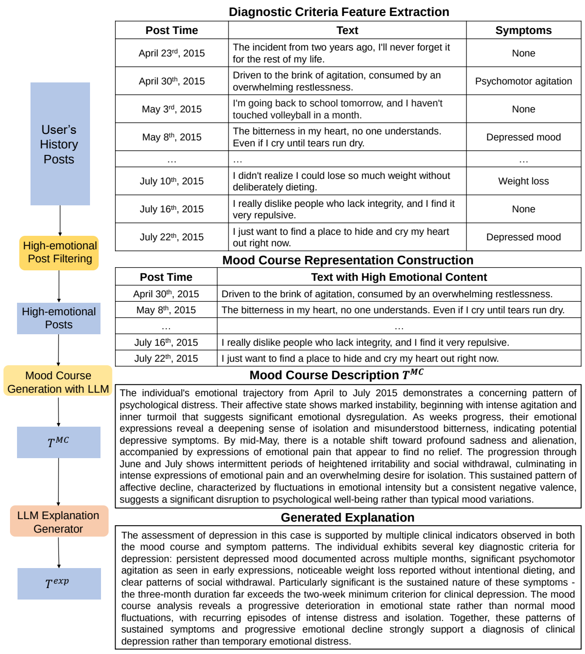

Figure 3: A case study of DORIS's output.

the SWDD dataset and demonstrates the robustness of our approach across different data sources.

4.2 DORIS's explainability (RQ2)

In our system, we annotate symptoms exhibited in users' posts, summarize the users' mood course, and based on these, provide explanations for the system's final decision output. An example is presented in Figure 3 to aid in better understanding the operation of our system. As seen, during the diagnostic criteria feature construction stage, our method accurately identifies depression-related symptoms in posts. In the mood course representation construction stage, our approach selects posts with high emotional density, thereby generating a mood course description. By combining identified symptoms of depression and the user's mood course, the system can generate evidence-supported explanations for its judgment. The DORIS system's accurate annotations of depression symptoms, detailed analysis of mood course, and the final evidence-supported explanations are all visible to mental health professionals. This allows the system to serve as a supportive clinical tool in depression assessment.

4.3 Ablation Study (RQ3)

In our method, the GBT classifier utilizes three constructed features: diagnostic criteria feature, mood course representation, and post history representation. We conduct ablation studies by removing each feature and observing the performance changes. The results are presented in Table 4.

Table 4: Experimental results of ablation study.

	F1-score	AUROC	AUPRC
Full Design	**0.7750**	**0.9722**	**0.8147**
w/o Diagnostic Criteria Feature	0.6867	0.9679	0.7739
w/o LLM Annotation	0.7028	0.9685	0.7861
w/o Mood Course Representation	0.7415	0.9660	0.7932
w/o Mood Course Summary	0.7635	0.9699	0.8035
w/o Post History Representation	0.7345	0.9660	0.7817

The results clearly indicate that the diagnostic criteria feature is the most critical component. Its removal causes the most substantial performance drop, with AUPRC decreasing from 0.8147 to 0.7739. This underscores the crucial role of integrating established medical knowledge. Within this module, the LLM-based symptom annotation is also vital; replacing it with a simpler template-matching approach (w/o LLM Annotation) still results in a significant AUPRC drop to 0.7861, demonstrating the LLM's superior ability to capture nuanced symptom expressions.

The post history representation, which provides a holistic view of a user's activity, is also highly impactful. Removing it leads to the second-largest performance decline (AUPRC of 0.7817), confirming its importance in capturing contextual information that more targeted features might miss. Finally, the mood course representation proves essential for modeling temporal emotional patterns. Its absence reduces the AUPRC to 0.7932, with its sub-component, the LLM-generated summary, also showing a clear contribution.

These results collectively demonstrate that each component of DORIS makes meaningful contributions to its overall performance, confirming the effectiveness of every part of DORIS's design.

5 Conclusion and Future Work

In this work, we present *DORIS*, a novel depression detection system that achieves high accuracy and interpretability by aligning with clinical diagnostic practices. The system integrates the widely used DSM-5 diagnostic criteria with analyses of mood course to deliver robust and explainable results. Extensive experiments validate the effectiveness of our method and the contribution of each design component. Future work will focus on pathways for real-world application, including integration with telehealth platforms and pilot studies within clinical settings to assess deployment efficacy and scalability.

Limitations

This work's primary limitation is its reliance on a focused set of datasets. While we validated our approach on two different datasets, further validation across more diverse data sources is necessary to ensure broader generalizability. Furthermore, while our experimental setup simulates a realistic pre-screening scenario (e.g., by using a 1:19 imbalance ratio), validation in a real-world clinical setting is the gold standard and a necessary next step for deployment. Finally, future research should extend this approach to other mental health conditions, such as anxiety and bipolar disorder, to broaden its clinical relevance and impact.

Ethics Statement

Our work on depression detection, a sensitive task, was guided by a strong ethical framework. We detail our primary considerations and mitigation strategies below.

Research Positioning and Intended Use. We position this work primarily as a Text Mining study aimed at extracting signals indicative of depression from unstructured text, aligning with established clinical criteria (DSM-5). We emphasize that this system is designed strictly as a *supportive tool* for qualified mental health professionals. It is not an autonomous diagnostic system and should never be deployed directly to end-users or used to make final clinical decisions. The explainable evidence provided (e.g., symptom annotations) is intended to help professionals verify risk signals. This "human-in-the-loop" model is key to mitigating the risks of potential model bias and error inherent in LLMs. Any real-world implementation must be supervised by practitioners and preceded by thorough validation from clinical experts.

Data Privacy and Security. All data was sourced from users who provided explicit consent for their content to be used in mental health research. To protect user privacy, we moderately obfuscated all examples in this paper per established guidelines (Bruckman, 2002). While our research utilized a commercial API, we have engineered the system to be deployable with secure, locally-hosted open-source LLMs, thereby eliminating the need to share sensitive patient data with third-party services in a clinical setting.

Risks of Misuse and Mitigation. We recognize the potential for misuse, such as exploiting emotionally vulnerable individuals or causing stigmatization. To mitigate these risks, we recommend strict access controls, limiting system use to licensed mental health professionals. Clear documentation of the system's capabilities and limitations is crucial to ensure it is used responsibly as a supportive aid.

Broader Societal Impact. While our system aims to augment mental healthcare, we acknowledge that technology alone cannot solve systemic healthcare disparities. It should be considered one component within broader initiatives to expand mental health resources. We also note that this paper contains descriptions of depressive symptoms that may be distressing for some readers. We are committed to the ongoing ethical evaluation of our system and encourage community discussion on the responsible deployment of such technologies. Further discussion on the practical design considerations for deployment can be found in Appendix E.

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A Related Works

A.1 Depression Detection on Social Media

Compared to traditional medical diagnostic methods for depression conducted in hospitals, depression detection on social media has the advantages of lower concealment potential, wider coverage, and lower cost (Malhotra and Jindal, 2022). Early research works first extract text features, then apply traditional machine learning methods for classification. Common feature extraction methods in depression detection research include LIWC (Tausczik and Pennebaker, 2010), TF-IDF, LDA (Blei et al., 2003), etc.; classifiers include SVM (Tadesse et al., 2019), Logistic Regression (Coppersmith et al., 2014), Random Forest (Cacheda et al., 2019), among others.

In recent years, deep learning technologies have seen wide application in depression detection. Methods utilizing CNN (Cohan et al., 2018) and RNN (Ive et al., 2018) have been developed to capture complex patterns in text. Pre-trained Language Models (PLMs) (Owen et al., 2020; Ji et al., 2023) have further improved performance by leveraging knowledge learned from large corpora. Graph Convolutional Networks (GCNs) (Naseem et al., 2022) have also been employed to model user interactions and behaviors. Notably, AMM-Net (Sarkar et al., 2022) introduced an a multi-task learning model that combines word embeddings and topic features to effectively predict depression and anxiety on Reddit. Follow-up work extended this approach using Graph-based Message-passing Multi-task learning (GMMTL) (Sarkar et al., 2023). These efforts have significantly improved the accuracy of depression detection, advancing the field's research.

Some works on depression detection focus solely on analyzing individual texts to determine the presence of depressive symptoms (Yang et al., 2022; Chiong et al., 2021), the type of symptoms displayed (Zhang et al., 2023a), and the level of depression (Zhang et al., 2023b). However, analyzing a user's post history is more informative, as it is common for individuals not suffering from depression to also occasionally post texts that exhibit depressive symptoms. Recent approaches to depression detection based on a user's post history (Eichstaedt et al., 2018; Orabi et al., 2018; Lin et al., 2020; Chiong et al., 2021; Yang et al., 2022; Sarkar et al., 2022) lack comprehensive integration of medical knowledge, limiting their accuracy and explainability. While some studies have attempted to introduce medical knowledge by considering clinical symptoms (Yadav et al., 2020; Nguyen et al., 2022), they do so through relatively ineffective methods such as keyword matching or vector similarity matching, which may miss complex expressions of symptoms. Our research stands out as one of the initial efforts to more systematically apply medical insights, leading to improved accuracy. Additionally, we are pioneers in employing LLMs to craft systematic explanations of predictions grounded in clinical evidence, thereby increasing explainability.

A.2 Large Language Models

Large Language Models (LLMs), possessing rich common-sense knowledge and human-like reasoning abilities, have achieved tremendous success recently. LLMs are being applied to a wide variety of domains, such as mathematics and reasoning (Xu et al., 2025; Hao et al., 2025b,a; HAO et al., 2024), text analysis (Hao et al., 2024; Lan et al., 2024b,a), user behavior modeling (Lan et al., 2025a,b), user simulation (Gao et al., 2023; Piao et al., 2025; Gao et al., 2024; Yan et al., 2025), code generation (Jimenez et al., 2023; Hou et al., 2024; Ross et al., 2023), and embodied intelligence (Brohan et al., 2023; Wang et al., 2025; Mon-Williams et al., 2025). Trained on vast amounts of human-generated text, LLMs have a strong potential to understand people, making them suitable for tasks like user behavior modeling and text comprehension. Consequently, they are also likely well-suited for tasks that require a deep understanding of human inner states, such as mental health analysis. Our work is among the first to explore this direction.

A.3 LLMs for Mental Health Analysis

Large language models (LLMs) have shown great potential in clinical applications due to its abundant prior knowledge and strong language generalization ability (Singhal et al., 2023). Recent works have introduced LLMs into mental health analysis. (Arcan et al., 2024) presents a solid evaluation on the performance of Llama-2 (Touvron et al., 2023) and ChatGPT (Ouyang et al., 2022) in mental health assessment tasks, unveiling prospects along with challenges of LLM-based methods. Yang et al. (2023a) further discover the applications of LLMs in both mental health detection tasks and reasoning tasks, which highlight LLM's excellent interpretability. Yang et al. (2023b) propose the first open-source LLM series for mental health analysis based on Llama-2 and fine-tuning techniques, and greatly enhances the accuracy and explanation quality compared with general-purpose LLMs. However, the challenge of LLM-based methods being weaker in terms of prediction accuracy compared to embedding model-based methods, especially when targeting specific downstream tasks, remains unresolved (Arcan et al., 2024).

To our knowledge, our system is among the first to be specifically designed for depression detection in the context of LLM for mental health analysis. Furthermore, we have facilitated a collaboration between LLMs and embedding models, attaining both high accuracy and explainability, addressing deficiencies in previous designs.

B Datasets

B.1 SWDD Dataset

Acquiring well-labeled, large-scale datasets for depression detection is challenging due to the sensitivity and privacy concerns associated with mental illnesses. Some datasets utilize self-reported medical diagnoses. While this approach offers relatively high reliability, it leads to datasets comprising users who are already medically diagnosed and willing to discuss it online. However, the most valuable aspect of depression detection task lies in assisting human experts to identify potentially undiagnosed users. Furthermore, the ratio of depressed to normal users in most previous datasets (Losada and Crestani, 2016; Zogan et al., 2021; Wu et al., 2023) is around 1:4 or even 1:1, deviating far from the actual prevalence of about 5% in the population.

To address these issues, we utilize the SWDD dataset (Cai et al., 2023). This dataset carefully adheres to strict ethical guidelines. It includes users who self-disclosed a diagnosis and those identified by experts as highly likely to be depressed based on medical criteria, but without self-disclosure. We retain these non-self-disclosing users and, after further expert screening, keep 1000 depressed users and 19000 normal users to simulate a real-world application scenario with a 1:19 ratio. We retain only the posts posted within six months prior to each user's last post. The dataset statistics are shown in Table 5. Training, validation, and test sets were divided in a 7:1:2 ratio, as recommended by (Wu et al., 2023).

B.2 Twitter Mental Disorder Dataset

To further validate the generalizability of our approach, we also utilized the Twitter Mental Disorder Tweets and Musics dataset. This dataset contains tweets from users diagnosed with various mental disorders, including depression, alongside a control group. We utilized the subset relevant to depression detection for our experiments.

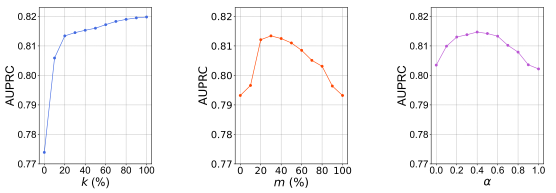
Table 5: Statistics of the SWDD dataset.

	Depressed	Control
Num. of users	1,000	19,000
Num. of posts	69,548	1,314,874
Avg. num. of posts per user	69.55	69.20

C Details of Comparison Methods

Here, we give a more detailed discussion of our utilized comparison methods.

- TF-IDF+XGBoost (Ramos et al., 2003; Chen and Guestrin, 2016; Wu et al., 2023): It uses TF-IDF weighted features of word and character n-grams for feature extraction, followed by XGBoost for classification.
- HAN (Yang et al., 2016): It obtains tweet-level representations through bidirectional GRU networks, and encodes all representations into user presentation with an attention mechanism.
- Mood2Content (Cai et al., 2023): This method utilizes knowledge distillation technology, transferring knowledge from an emotion classifier to depression detection.
- AMM-Net (Sarkar et al., 2022): An attention-based multi-view and multi-task learning framework that integrates different feature perspectives and jointly optimizes for related mental health conditions (e.g., depression and anxiety).
- FastText (Joulin et al., 2016), gte-small (Li et al., 2023), BERT (Devlin et al., 2018), Mental-RoBERTa (Ji et al., 2023): These models are used to obtain text embeddings. We compute the average embedding across all posts to generate a user-level representation, which is then fed into a tree classifier.
- PHQ9 (Score) and PHQ9 (Vector) (Nguyen et al., 2022): PHQ9 (Score) uses BERT to classify the 9 symptoms of PHQ-9, and then uses these symptom scores as features input to a CNN classifier.



(a) Impact of k. (b) Impact of m. (c) Impact of α.

Figure 4: Results of hyperparameter study.

PHQ9 (Vector) uses the hidden layer vectors of the PHQ-9 symptom classifiers as features.

- GPT-4o mini, MentalLLaMA (Yang et al., 2023b): For LLM-based approaches, we design prompts following Yang et al. (2023a). We input the user's tweet history to the LLM, and then ask the LLM to classify.

D Hyperparameter Study (RQ4)

In our method design, we introduce four hyperparameters: k (proportion of text for LLM annotation), m (proportion of emotionally intensive text), and α and β (ratio between LLM analysis and original posts in mood course representation). The experimental results are shown in Figure 4.

Impact of k. As k increases, the AUPRC monotonically increases. Annotating 20% of the text with the LLM significantly improves AUPRC and is close to the performance when all texts are annotated. This demonstrates the rationality of our design for efficient implementation.

Impact of m. As m increases, the AUPRC initially rises and then falls, suggesting a trade-off between capturing emotionally intensive posts and retaining sufficient information.

Impact of α and β. When α:β ratio is 2:3, the system achieves optimal performance.

E Practical Design Considerations

Our research is motivated by the real-world need to address the global shortage of mental health services. Literature indicates an urgent need for effective, automated tools to assist with large-scale, low-cost early screening, complementing the efforts of human professionals (Whitton et al., 2021; Balcombe and De Leo, 2021). The design philosophy of DORIS is guided by deployability and considers several practical constraints:

Cost and Efficiency. We designed an efficient filtering mechanism (Section 2.2.2) to significantly reduce expensive LLM API calls. As shown in the hyperparameter study (Appendix I), annotating only 20% of the text achieves performance close to full annotation. This is a critical consideration for large-scale deployment.

Privacy and Flexibility. In addition to using APIs, we validated our framework's effectiveness with locally deployed open-source LLMs (Appendix J). This directly addresses the core concerns of data privacy and security in real clinical settings and demonstrates deployment flexibility.

Explainability. For medical applications, we view explainability not just as an academic pursuit but as a core prerequisite for gaining trust from clinicians and driving adoption. The hybrid design ensures that the system provides concrete evidence aligned with clinical practice.

F Prompt Instruction

The following prompt is used to instruct the LLM to identify depression symptoms within a given post:

> *Assuming you are a psychiatrist specializing in depression. Given [text], please determine if this message includes any of the following states of the author:*
> *A. Depressive mood B. Loss of interest/pleasure ... I. Thoughts of suicide.*
> *If present, answer in the format of enclosed letters separated by commas, for example, (A, B, C). If none are present, respond with None.*

The following prompt is used to instruct an LLM to synthesize a description of user u's mood course, T^{MC}:

> *"As a consulting psychiatrist, please conduct a longitudinal mood course analysis based on the following temporal sequence of personal expressions. For each entry, evaluate affect, emotional valence, and severity of mood states. Synthesize these observations into a clinical summary of mood progression, noting any patterns of persistence, fluctuation, or changes over time:*
> *Time: t_1, Post: p_1, Time: t_2, Post: p_2, ..."*

The following prompt is used to instruct the LLM to generate the explanation text, T^{Exp}:

> *"Assuming you are a psychiatrist specializing in depression.*
> *Here is a user's mood course: T^{MC}; below are posts from this user displaying symptoms of depression and the types of symptoms exhibited: ...; this user has been determined by an automated depression detection system to be depressed/normal.*
> *Please consider the user's mood course and posts to generate an explanation for this judgment. Your explanation should be grounded in concrete evidence."*

G Symptom Templates

During the Diagnostic Criteria Feature Extraction phase, with the assistance of clinical psychologist and psychiatrists, we designed symptom templates to filter text with a high likelihood of depression through matching. Specifically, the templates we designed are as follows:

A. Depressed mood. I feel low, unhappy, joyless, depressed, oppressed, gloomy, disappointed, melancholic, sad, distressed, heartbroken, a sense of loss, often feeling heavy-hearted, experiencing despair and despondency, always feeling sorrowful with an urge to cry, experiencing inner pain and emptiness.

B. Loss of interest/pleasure. I have lost interest, feel indifferent, bored, unconcerned, lack enthusiasm, am unmotivated, have no interest in activities, am unmotivated, find almost everything uninteresting, lack motivation, find significantly reduced pleasure, cannot experience happiness, feel the world is dull, and cannot muster energy all day.

C. Weight loss or gain. I experience reduced appetite, often feel full, lack of appetite, nausea, abnormal weight loss, difficulty swallowing, emaciation, loss of appetite, poor appetite, weight loss, or abnormal weight gain, sudden weight increase, unexplained weight gain.

D. Insomnia or hypersomnia. I suffer from sleep disorders, depend on sleeping pills, often experience insomnia, have difficulty falling asleep, rely on sleep medication, frequently stay up late, struggle with sleep difficulties, and exhibit symptoms of insomnia, tossing and turning at night, or hypersomnia, oversleeping, sleep excess, prolonged sleep duration, or excessive sleepiness.

E. Psychomotor agitation or retardation. I am neurotic, easily agitated, emotionally unstable, impatient, anxious, restless, mentally tense, irritable, often feeling mentally uneasy and agitated, fidgety, displaying impulsive and irritable behavior, and my emotions are easily out of control.

F. Fatigue I feel fatigued, listless, exhausted, physically weakened, lacking in energy, dispirited, frequently tired, powerless, often feeling weary, unable to muster strength, feeling a heavy body, lacking in vitality and vigor, always feeling drowsy and lethargic.

G. Inappropriate guilt. I have feelings of self-denial, lack of confidence, self-doubt, inferiority, disappointment, guilt, negative self-evaluation, self-blame, frequently belittle myself, feel incompetent and worthless, believe that I have achieved nothing and am a failure, feel disappointed in my expectations of myself and my family, often feel guilty and blame myself, thinking that everything is my fault.

H. Decreased concentration. I experience slow thinking, difficulty concentrating, reduced judgment, memory decline, distractibility, indecision, scattered attention, difficulty thinking, lack of focus, difficulty paying attention, decreased cognitive ability, hesitancy in making decisions, often feeling mentally spaced out, unable to concentrate.

I. Thoughts of suicide. I have a desire for death, self-harming behavior, suicidal thoughts, thoughts of ending my life, suicidal actions, thoughts of suicide, self-injury, recurring thoughts of death, suicidal tendencies, self-mutilation, cutting wrists with blades, jumping from heights to commit suicide, overdosing to commit suicide, making plans for suicide.

H Emotion Templates

During the Mood Course Representation Construction phase, with the assistance of clinical psychologist and psychiatrists, we designed emotion templates. The purpose of emotion templates is to filter text with a high emotional intensity to generate the user's mood course. Specifically, the templates we designed are as follows:

1) Anger I am angry, mad, agitated, annoyed, indignant, irritable, furious, disgusted, incensed, enraged, irritated, vexed, resentful, in a rage, glaring, shouting, screaming, insulting, hating, bellowing, outraged, ranting, detesting, fuming, and uncontrollably angry.

2) Disgust I detest, loathe, disgust, abhor, hate, tire of, feel nauseated by, have a strong aversion to, despise, scorn, disdain, reject, find repugnant, utterly dislike, disdain, feel revulsion, despise, dislike intensely, abominate, have a strong displeasure, grow weary of, become impatient with, dismiss, look down upon, and utterly abhor.

3) Anxiety I feel anxious, uneasy, worried, concerned, nervous, restless, panicked, fretful, afraid, uncertain, apprehensive, tense, jittery, indecisive, fearful, flustered, melancholic, frightened, apprehensive, full of doubts, brooding, terrified, distrustful, terrified, and on edge.

4) Happiness I am happy, joyful, glad, blissful, merry, satisfied, delighted, elated, pleased, laughing, cheerful, excited, jubilant, optimistic, enthusiastic, cheerful, uplifted, exuberant, overjoyed, jubilant, with a smile on my face, pleasantly surprised, beaming with joy, and my heart blooms with happiness.

5) Sadness I am sad, sorrowful, melancholic, in pain, lost, depressed, pessimistic, tearful, grieving, mournful, depressed, suicidal, heartbroken, devastated, upset, crying, deeply saddened, disconsolate, dejected, lamenting, desolate, gloomy, mournful, weeping bitterly, desperate, heartbroken, indignant.